

AD-A215 619



DTIC FILE COPY

AN EVALUATION OF THE AIR FORCE
INSTITUTE OF TECHNOLOGY
STUDENT SELECTION CRITERIA

THESIS

KEVIN W. BUCKLEY

CAPTAIN, USAF

AFIT/GSM/LSR/89S-2

DISTRIBUTION STATEMENT A

Approved for public release;
Distribution Unlimited

DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY

AIR FORCE INSTITUTE OF TECHNOLOGY

DTIC
ELECTE
DEC 20 1989
S a E D

Wright-Patterson Air Force Base, Ohio

89 12 19 015

AFIT/GSM/LSR/89S-2

AN EVALUATION OF THE AIR FORCE
INSTITUTE OF TECHNOLOGY
STUDENT SELECTION CRITERIA

THESIS

KEVIN W. BUCKLEY

CAPTAIN, USAF

AFIT/GSM/LSR/89S-2

APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED

The contents of the document are technically accurate, and no sensitive items, detrimental ideas, or deleterious information is contained therein. Furthermore, the views expressed in the document are those of the author and do not necessarily reflect the views of the School of Systems and Logistics, the Air University, the United States Air Force, or the Department of Defense.

Accession For	
NTIS GRA&I	<input checked="checked" type="checkbox"/>
DTIC TAB	<input type="checkbox"/>
Unannounced	<input type="checkbox"/>
Justification	<input type="checkbox"/>
By	
Date	
Limit	
A-1	

AFIT/GSM/LSR/89S-2

AN EVALUATION OF THE AIR FORCE INSTITUTE
OF TECHNOLOGY STUDENT SELECTION CRITERIA

THESIS

Presented to the Faculty of the School of Systems and
Logistics in the Air Force Institute of Technology

Air University

In Partial Fulfillment of the
Requirements for the Degree of
Master of Science in Systems Management

Kevin W. Buckley, B.S. B.S.

Captain, USAF

September, 1989

Approved for public release; distribution unlimited

Acknowledgments

I extend my most sincere appreciation to my thesis advisor, Dr. Guy Shane, for his insight, advice, encouragement, and overall outstanding support. Without his aid, this thesis would not exist today.

I also gratefully acknowledge the assistance given me during the data collection. My gratitude goes out to Captain Steve Gurnell and his entire staff in the records branch of the AFIT Registrar's office for their help and friendliness.

I am especially indebted to my fellow students who not only made this AFIT experience bearable, but also enjoyable. Special thanks go out to Ken (Rojo Grande) Hahn, Mark (the Beast) Schenning, John (Peanut) Loschiavo, Donny (Wu Wu) Wussler, Rod (Guzman) Motley, Ricky Lemaster, Clay (Porcupine) Frasier, Alan (AJ) Johnson and Mack Thorn. Gentlemen, thanks to you this has definitely been an outstanding learning experience. Special mention also goes to Lauri Smith who helped me learn more about myself. Finally, thanks go to my family, without whom, none of this would have been possible.

Kevin W. Buckley

Table of Contents

	Page
Acknowledgments	ii
List of Tables	v
Abstract	vi
I. Introduction	1
General Issue	1
Problem Statement	4
Literature Review	5
Reliability	6
Validity	7
Predictors	13
Criteria	14
Research Hypotheses	18
II. Methodology	19
Introduction	19
Subjects	19
Definitions of Variables used	19
Criterion Variable	21
Predictors	21
Data Collection	22
Data Analysis	24
III. Results	28
Introduction	28
Correlation Results	28
Regression Results	39
IV. Conclusions	41
Introduction	41
Hypothesis Review	41
Discussion	42
Conclusions	46
Suggestions for Future Research	47
Summary	48
Appendix A: Frequency Distributions for Criterion and Predictor Variables	49

	Page
Appendix B: Descriptive Statistics for Criterion and Predictor Variables By Program	59
Appendix C: Multiple Regression Prediction Models	82
Bibliography	107
Vita	111

List of Tables

Table	Page
1. Acronyms and Definitions of Variables	20
2. Descriptive Statistics for Entire Sample	23
3. Correlation of Predictors with GGPA for Entire Sample	29
4. Significant Predictors for Each Program	31
5. Prediction Models for GGPA	40
6. Summary of Number of Programs (By School) in which Predictor is Significant	44

Abstract

This thesis was designed to evaluate the suitability of the variables that AFIT currently uses to select graduate students. The objective was to determine if, indeed, these variables are effective at predicting graduate school academic success at AFIT.

The study examined the records of 4170 US military officers, foreign officers, and civilians who attended in-residence AFIT graduate programs from 1977 to 1987. From these records was obtained data on each students' undergraduate GPA and scores on standardized tests, which AFIT currently uses in the selection process.

Using the graduate GPA as the criterion, this study examined the effectiveness of these predictors with correlation analysis. In addition to studying the student population as a whole, the sample was also broken down to see if the predictors were equally suitable across all programs.

The study found that all predictors were significantly correlated with graduate GPA and thus were suitable for use in the selection process. In addition, the study found that all predictors were not equally effective in predicting academic performance in all programs. Using the best set of significantly correlated variables, predictive models were developed for each program. The admissions office should use each model to select students on a program-by-program basis.

AN EVALUATION OF THE AIR FORCE INSTITUTE OF TECHNOLOGY STUDENT SELECTION CRITERIA

I. Introduction

General Issue

With the increasing use of highly technical and complex systems to counter potential threats, the Air Force has created significant demand for officers capable of creating, developing, maintaining, and using these systems. It is the mission of the Air Force Institute of Technology (AFIT) to provide education and training in order to satisfy these requirements. By giving its students the broad educational background needed to understand the cultural and technological environment, AFIT attempts to give them the ability to analyze and solve complex technical and managerial problems. AFIT performs two distinct services: providing professional continuing education and training programs and conducting graduate and undergraduate degree curricula. This study, however, is concerned solely with the graduate degree programs.

Although AFIT arranges for some of its graduate students to attend programs at civilian institutions, it does conduct selected degree programs in residence. The majority of these in-residence graduate degree programs are conducted at one of two schools. The first of the two, the AFIT School of

Engineering and Services, focuses on technology and state-of-the-art. Its programs include aeronautical engineering, astronautics, electrical engineering, systems analysis, operations research, and engineering physics. The second, the AFIT School of Systems and Logistics, concentrates on the art of management. Its programs include logistics management, contracting and acquisition management, acquisition logistics management, international logistics management, engineering management, and systems management (10:13).

Not every Air Force officer attends AFIT, however. Due to funding restrictions and class-space limitations, admissions to in-residence graduate programs are limited to several hundred per year. Competition for these opportunities is tough and, in order to select the most highly qualified students, rigorous selection procedures have been instituted. However, unlike a civilian graduate institution that selects the most highly qualified individuals strictly on the basis of their academic record with no advice from any outside organization, AFIT receives its students based upon the decisions of the Air Force Military Personnel Center (AFMPC). For entry to AFIT, both military job performance and previous academic achievements are considered as selection criteria.

Officers wishing to apply for an AFIT degree program must first request an evaluation of their academic background. This evaluation, performed by the AFIT

Registrar's office, measures the officers academic record against both general and program specific eligibility criteria. For most AFIT graduate programs, this includes a minimum undergraduate grade point average of 2.50 (out of 4.00) and satisfactory completion of an appropriate graduate admissions test. If the officer meets this general eligibility criteria, and any specific criteria for the program in which they desire to study, they are issued a letter of eligibility. A copy of this letter is placed in their master personnel files at AFMPC. As only officers with letters of eligibility are considered by AFMPC for AFIT assignments, this evaluation is the school's means of ensuring that only qualified students are selected to attend. AFMPC then selects students based upon military job performance, assignment availability, promotability, post-AFIT assignment suitability, and other factors (10:17). This selection process "has been designed to select officers whose potential contributions after graduation will most benefit the Air Force" (10: 16). Thus, AFIT has little control over which particular students will be admitted in any given year; the school only identifies to AFMPC a group of potential students it is willing to accept. In essence, AFIT selects the students and AFMPC decides when they will attend, if ever.

AFIT also differs from civilian institutions with regard to tuition. There is no tuition to attend AFIT; the costs are borne completely by the government. According to a 1982

AFIT financial report, the Air Force spends at least \$65,000 to send a student through a resident graduate program (1:5). Since a significant amount of money is invested in each student, it would behoove AFIT to adopt a highly selective, and highly reliable, admissions policy in order to maximize the return on this investment. This, of course, assumes that a student who does not graduate has taken an opportunity from a student who may have graduated. Thus, the AFIT Registrar's office should employ an admissions policy that uses predictor variables that are both reliable and valid. This will enable them to come as close as possible to a 100% graduation rate. Since, as discussed above, AFIT currently uses undergraduate grade point averages and scores on standardized tests as predictors for academic performance, the validity of these predictors must be evaluated.

Problem Statement

The primary purpose of this thesis is to evaluate the effectiveness of several variables that AFIT uses as predictors of academic performance for U.S. military officers, foreign military officers and civilians in graduate programs. These variables will include standardized test scores such as the GRE and GMAT and undergraduate grade point average. These variables may be combined to build a predictive model to be used for future AFIT admissions. If necessary, different models will be developed for different graduate programs.

Literature Review

A discussion of the basic concepts of testing and measurement will serve to familiarize the reader with the concepts of validation.

A physical scientist who wishes to know more about a certain object will use his instruments to measure it. Regardless of whether the instrument is a ruler or an infrared spectrograph, the object's physical characteristics can be measured with precise and uncontroversial techniques. However, the behavioral and social sciences are fundamentally different from the physical sciences. According to Green, this difference lies in the fact that not only are concepts difficult to measure but sometimes there is disagreement over the meaning of the concepts themselves (16: 1002). He uses the concept of intelligence as an example. Not only is the measurement of intelligence disputable, but it has no universally agreed upon definition. It is the presence of constructs such as this in the behavioral sciences that bring about a need for evidence that the intended characteristics are actually being measured by a test (16: 1002).

A standardized test is an examination, given under specified conditions, which is designed to measure some aspect of an individual's knowledge or personality. Because the same test can be given under the same specified conditions, it can provide a scale for the assessment of consistent individual differences regarding the concept that the test has been designed to measure. Although it may be

difficult or impossible to determine an absolute measure of a specific individual's trait, the standardized test does serve well to provide a relative scale for comparing many individuals' traits. Thus, the object of the test is to provide fair comparison among the test takers. In graduate school admissions, standardized tests provide a common measure for all potential students. However, for these test scores to be useful for student selection, they must exhibit both reliability and validity (16: 1005).

Reliability. Reliability can be described as the extent to which test scores are repeatable and stable. Simply put, reliability is concerned with the degree to which a measurement is free of random error. The key word here is random. For example, a timepiece which consistently runs ten minutes fast is highly reliable but hardly valid. On the other hand, a timepiece which randomly runs both slow and fast is neither reliable nor valid (17: 28).

As the minimization of randomness is the key to any reliable test, reliability can be expressed as the extent to which a test consistently measures whatever it does measure. In the case of a standardized test used for admissions, reliability could be defined as the extent to which a student repeating the test would tend to receive the same score (assuming, of course, that taking the same test more than once adds nothing to the score achieved).

Reliability can be estimated by correlating students' test scores with their scores on an equivalent test. The

resulting correlation coefficient is an estimator of the test's reliability. This coefficient reveals the degree to which individuals tested as a group keep the same relative standing when two equivalent forms of the test are given. If there is no change in the relative standings, the reliability coefficient would be 1.00. When evaluating individuals for selection to graduate school, the Educational Testing Service considers reliability coefficients of 0.90 or above as satisfactory (13: 24). That is, for standardized tests, such as the GRE (which is administered by the Educational Testing Service), the reliability coefficients should be at least 0.90 in order to use scores on that test as a graduate student selection criterion. The GRE verbal and quantitative tests exhibit reliability coefficients of 0.93 and 0.90, respectively (13: 24).

In order to accurately interpret the results of a correlation between predictor variables and a certain criterion variable, it is necessary to ensure that they are all reliable. In order to measure this reliability, Dick and Haggerty offer three basic procedures. To compute the reliability coefficient, a test may be given twice (with the testing separated by some interval of time), an alternative form of the test may be given after a period of time, or a test may simply be given once (11: 18-19).

This first method of estimating reliability is called the test-retest procedure. Here, the reliability of the test is expressed as the correlation between the scores of the

same test given twice to the same students. This technique is used to with the hope that at the second testing the test takers will not remember their earlier responses.

The second procedure for estimating reliability is the alternate forms method. Here, the estimate is obtained by correlating the scores obtained by students on two different forms of the same test. This method corrects the weaknesses of the test-retest method in that the same items do not appear on both tests. However, the results of this procedure can be influenced by the effects of boredom and fatigue on the part of the student or by the amount of time between the two tests (11: 21).

The third method for establishing the reliability of a test score involves giving the test once and using statistical methods to determine its internal consistency. One way to accomplish this is the split-halves procedure. Here, the test is divided into two equivalent halves that are timed separately. The only difference between this method and the test-retest method is in the length of the halves. By using the Spearman-Brown formula:

$$R = 2r/(1+r) \quad (1)$$

the reliability of the total test, R , can be estimated from the correlation of the two halves, r .

This Spearman-Brown formula is derived from the classical theory of testing. This theory asserts that a test

score is made up of two components and can be represented by the equation

$$X_o = X_t + X_e \quad (2)$$

In this equation, X_o is the score obtained by the test-taker, X_t is the true component of the person's score which is devoid of random error, and X_e is the error component. Since the true score, X_t is a hypothetical construct, it cannot be observed. However, since the true score is independent of the errors, the variance of X_o is the sum of the variances of X_t and X_e . With two equivalent halves, the true score will be doubled while the errors tend to cancel each other out due to randomness (16: 1005).

Another procedure for assessing a test's internal consistency is based upon the intercorrelations of the individual items on a single test. Actually, this is the application of the classical test theory on the item level. Each item is viewed as a miniature test with both true and error components. Since the errors are random, and therefore uncorrelated, the correlation among items depends only on the true component (16: 1006).

Validity. Validity is concerned with how accurately an instrument measures what it is intended to measure. Emory further defines validity as "the extent to which differences found with a measuring tool reflect true differences among those being tested" (14: 94).

The process of validation can have many different aims. Validity can be separated into three types. The first, content validity, is the extent to which the test or measuring tool covers a representative sample of the population under study. The second, construct validity, deals with the relationship between a theory and actual performance. The third type, criterion-related validity, is the effectiveness with which a test or measurement can predict an individual's behavior or the outcome in a causal relationship. Actually, criterion-related validity can be subdivided into concurrent validity and predictive validity. Anastasi differentiates between concurrent and predictive validation on the basis of the time relationship between the criterion and the test. A political survey that correctly forecasts the winner of an upcoming election has predictive validity (2: 131-137). On the other hand, concurrent validity, which Emory also calls "immediate predictive validity" (14: 89) is determined by correlating measurements with information which is currently or immediately available. Lent advises the use of concurrent validation studies, if possible, versus predictive ones. This is because concurrent validation studies, with their near-simultaneity with respect to the relationship between predictor and criterion, minimizes the effect of external influences upon the measured association (21: 527). Unfortunately, in most cases the criterion is not available at the time of testing thus eliminating the possibility of a concurrent study.

The correlation between a predictor and the criterion results in a validity coefficient. The numerical value of this coefficient represents a measure of the efficiency of the predictor when used for selection purposes. A predictor with a correlation of 0.0 with the criterion represents zero efficiency, or random selection. Similarly, a correlation coefficient of 1.0 represents as good efficiency as is possible from using the criterion itself as the selector (5: 66-67). This coefficient is actually a numeric index of the validity of that predictor.

Chronbach points out that a positive coefficient reflects the increased accuracy that results from using that predictor, based on the test results, as compared to random guessing. In other words, an improvement in selection can be expected from the use of a predictor over what would be expected from the use of the criterion alone. However, Chronbach warns that considerations such as the cost of the testing, the urgency of improved selection, and the cost and validity of the selection method already in use should all be weighed prior to any new testing (8: 133). In addition, Anastasi maintains that prior to drawing any conclusions from a test, the tester should have reasonable certainty that the observed validity coefficient is statistically significant. Could the validity coefficients have arisen through random fluctuations of sampling and be small enough to ignore or could this be a fluctuation of a coefficient that is truly zero (2:159)?

There are several factors which tend to affect the size of the validity coefficient. The most significant is restriction in range, a phenomenon that occurs when the sample group is homogeneous compared to the general population. As the range of the predictor becomes narrower, it becomes more difficult to differentiate between members of the sample, thus artifactually reducing the coefficient (8: 135). This definitely becomes a factor when studying predictors of graduate academic success. In these studies, restriction in range tends to reduce validity coefficients when correlating standardized test scores, such as the GRE, and graduate grade point averages (GPA). This is because the range of GRE scores within the sample is significantly smaller than the range occurring in the general population (34: 476). This can be attributed to the fact that students with low GRE scores were not accepted into graduate school in the first place. In addition, the poorer students probably didn't even take the GRE thus further lowering the variability of the scores. Therefore, a study which uses GRE scores as a predictor for graduate academic success will experience lower validity coefficients due to the reduced range of the predictor. A necessary, but not sufficient condition, for a high validity coefficient is the combination of a large and heterogeneous population and wide ranges of measured characteristics for both the predictor and the criterion (13: 16).

predictors. Many studies have been conducted in an effort to validate predictors of academic success in graduate school. The majority of these studies have used standardized test scores as the primary predictor. These studies include Nagi (28: 471), Borg (4: 380), Camp and Clawson (7: 429), Robertson and Nielsen (30: 649) and Michael, Jones and Gibbon (26: 859).

Thacker and Williams summarized the results of twelve such studies, conducted from 1957 to 1970, which all used the GRE as the primary predictor of graduate academic success. Most of the studies reviewed by Thacker and Williams exhibited low correlation coefficients, although the use of graduate GPA, with its inherent shortcomings (as discussed in the next section), as the criterion variable may have been partially responsible (32: 942-944). Choice of the criterion variable aside, the results certainly suggest that the use of the GRE alone, as a predictor, should be subjected to further analysis or additional predictors should be posited.

At least two recent studies, however, have used multiple predictors in an effort to improve predictive ability. Van Scotter and Bruno both used standardized test scores in addition to other variables such as undergraduate GPA, number of years of commissioned service, and number of undergraduate math courses in attempts to predict graduate student success of military officers. Even though significant coefficients were obtained, both studies agreed that additional analysis is warranted (6: 21, 35: 38). The published literature

agrees with this approach. Lin and Humphreys (22: 250), Covert and Chansky (9: 947), Mehrabian (25: 410), and Baird (3: 943) all report significant findings as a result of using more than one predictor variable.

Although many different predictors of graduate academic performance are available, whichever is chosen should be re-validated periodically (20: 819).

Criteria. Prior to conducting any statistical tests to determine the criterion related validity of any predictor variables, it is necessary to determine the criterion against which the predictors will be correlated. In Thacker and William's review of twelve studies of the GRE as a predictor for academic success, ten of the studies used some form of the graduate GPA as the primary criterion variable. In the other two studies, one used faculty ratings and the other used pass/fail Doctoral comprehensive exams as the criterion variable. In this review, the authors echoed Borg's warning on the use of graduate GPA as the criterion variable. The basis for this warning was the low discrimination of this measure; that is, graduate grades tend to be artificially restricted to the A to B range. It is interesting to note, however, that Thacker and Williams also recognized in this review that "the use of other criteria did not consistently yield improved correlations" (32: 943).

Chronbach realized the importance of choosing the correct criterion when he declared that the most difficult aspect of predictive validation is obtaining appropriate

criterion data (8: 122). In fact, Michael, in his review, even noticed that "One reason frequently given for the absence of higher validity coefficients than those usually obtained has been the lack of reliability of the criterion (26: 56)". When attempting to quantify graduate academic success, several criterion variables are available. Graduate GPA, as observed above, is most prevalent. However, researchers have also used a graduated/failed to graduate dichotomy, faculty ratings, and rated success after a specified time period as alternate criterion variables.

Hartnett and Willingham discussed several alternative criteria for graduate academic success and also observed the strengths and limitations of each. In their investigation, they found graduate school grades to be the most popular criteria for academic success. There are numerous reasons for this popularity. First, graduate grades represent the faculty's view of student performance. No one is in a better position to gauge the student's progress than their faculty. Secondly, as a criterion variable, graduate grades exhibit significant stability and consistency from semester to semester thus increasing the reliability coefficient. Thirdly, graduate grades are attractive as criterion variables because they are available soon after the student starts the program. This avoids the lengthy wait for the variable which is indicative of other criteria, such as post-graduation employment performance evaluations (18: 13). Also, Livingston and Turner cite the fact that graduate

grades are used in every program as another attractive feature of using them as the criterion variable (23: 2).

The published literature seems to support the use of the graduate grade point average as a popular criterion variable. The majority of the studies reviewed used graduate GPA in their analyses. These include Borg (4: 380), Madaus and Walsh (24: 1105), Eckhoff (12: 484) and Sleeper (31: 1039).

The use of graduate GPA as the criterion is not without its difficulties, however. Hartnett and Willingham cite restriction in range problems when using this criterion. Since graduate grades exhibit such a narrow range (generally, they are artificially restricted to the A to B range), this attenuates the validity coefficients. In addition, grading standards can and do vary dramatically, even between programs in the same school. Finally, the abstractness of the grades causes difficulties. Even to the student who receives them, it is not always clear what the grades mean. Therefore, while grades serve useful purposes in graduate education, most notably as motivators of performance and statements of student achievement, they are less useful as an unambiguous criterion for graduate student performance (18: 11-14).

Degree attainment was also discussed as a possible criterion for graduate student performance. Since it is a binary variable, it avoids the abstractness of grades. By administrator's standards, it is the single most important criterion of success in graduate education. Another advantage is that graduate students themselves clearly regard

it as the most important outcome of their studies. Even though the use of degree attainment is much less ambiguous than the use of grades, it, too, has its limitations. Most significant of these disadvantages is the fact that students drop out of graduate school for many reasons, many of which have little to do with academic ability. Thus, even though a student may be academically successful, he could still be counted as a failure by this measure (18: 15-18).

Willingham identifies faculty ratings as another useful criteria frequently used in validity studies. Their single biggest advantage is that they are relatively easy to obtain, thus providing a convenient criterion. However, they still suffer from some serious shortcomings. The most troublesome is that faculty members tend not to be familiar enough with the student's work to make an informed rating. Of course, this depends most upon the size of the program. As with grades, ratings suffer from problems with leniency and range restriction (36: 273-275).

These difficulties did not stop all researchers from using this criterion variable, however. King and Besse (1981: 855), Michels (27: 860), and Robertson and Hall (29: 301) all report significant correlation coefficients between faculty ratings and their respective predictor variables.

The conclusions reached by Hartnett and Willingham include the fact that insufficient research has been done on what exactly constitutes successful academic performance. This can be directly related to the fact that many graduate

faculty members place very low priority on efforts to evaluate student performance outside the existing practices. If this can be turned around, perhaps a useful criterion can be discovered (18: 38).

Guion advises careful thought prior to choosing the criterion variable:

Careful criterion development rests upon the answers to several questions. Should there be one criterion covering all aspects of performance, or should there be many independent, unitary criteria? What are the objectives of the organization, and how does a given job fit into these objectives? Conceptually, what are the basic variables along which performance--and the success of the selection program specifically--can be evaluated? (17: 112)

In essence, Guion counsels that whatever criterion is chosen, it should not be simply because it was available.

Research Hypotheses

1. Standardized tests, such as the Graduate Record Examination and the Graduate Management Admissions Test, are valid predictors of AFIT graduate school performance.
2. Undergraduate grade point averages are valid predictors of AFIT graduate school performance.
3. The correlations of the predictors and the criterion variable will vary between graduate degree programs.
4. The above variables can be combined into predictive models which produce significant results.

II. Methodolgy

Introduction

This chapter describes the method by which this analysis was conducted. The subject population was identified, suitable criterion and predictor variables were chosen, and data was collected. After data collection was complete, statistical analyses were conducted to reduce the data to meaningful information.

Subjects

The sample in this study consists of all U.S. military officers, civilians, and foreign officers who attended AFIT graduate programs in the School of Engineering or the School of Systems and Logistics between 1977 and 1987. The size of this sample is 4170 students.

Definition of Variables Used

Table 1 provides the acronyms for and defintions of all variables used in this study. Undergraduate grade point averages (UGPA) are on a 4.00 scale. Some undergraduate institutions grade their students on other than a 4.00 scale which required a correction to the reported average. In addition, most foreign students were evaluated under a pass/fail system which effectively resulted in unreportable grade point averages.

Table 1

Acronyms and Definitions of Variables

ACRONYM	DEFINITION
YEAR *	Last two digits of calendar year of AFIT graduation
PROG *	Master's degree program which student graduated from
GGPA	AFIT graduate grade point average
NAT *	Nationality of student
UGPA	Cumulative grade point average from all undergraduate schools attended by student
GREV	Student's score on the GRE Verbal Aptitude test
GREQ	Student's score on the GRE Quantitative Aptitude test
GRET	Student's total score on the GRE Aptitude test (GRET = GREV + GREQ)
GREA	Student's score on the GRE Analytical Aptitude test
GMATV	Student's score on the GMAT Verbal test
GMATQ	Student's score on the GMAT Quantitative test
GMATT	Student's total score on the GMAT
TOEFL	Student's score on the Test of English as a Foreign Language

* denotes an indicator variable

Criterion Variable

The criterion variable chosen for this thesis , used to measure graduate academic performance, was graduate GPA. As noted in the literature review, this criterion variable has been used successfully in many previous studies in spite of its limitations.

Although teacher ratings or post-school job performance (15: 638, 18: 32) would have alleviated some of the limitations characteristic of GGPA, the use of this type of data was infeasible for this study. In the case of the former, acquiring teacher ratings of students who graduated up to ten years ago was almost impossible. This was due to the fact that many of the instructors at AFIT are military personnel who get reassigned every four years and locating them now would be very difficult.

In the case of the latter, the only accessible document which reviews post-school job performance is the Officer Effectiveness Report (OER) which an officer receives annually. Unfortunately, this report has been accused of being a positively biased review of the officer's achievements and therefore would not be very reliable. In addition, OERs are not available on civilians or foreign officers.

Predictors

The predictors used in this study will be the same predictors which the AFIT registrar's office uses to select

its students. They are undergraduate grade point average (UGPA), scores on the Graduate Record Examination (GREV, GREQ, GREA, and GRET), scores on the Graduate Management Admissions Test (GMATV, GMATQ, and GMATT), and, for foreign students, scores on the TOEFL. Any other possible predictors were not chosen because they are not used in the student selection process and therefore would be superfluous to this analysis.

Data Collection

The data used in this study was collected from the student files located in the AFIT registrar's office (AFIT/RR). In addition, only the information which was available to the selection committee at the time of eligibility determination was used in the analysis. For example, if the student re-took the GRE after graduation and achieved significantly higher scores, only the lower, earlier GRE scores were used. This is logical because it was the lower scores by which the student's eligibility was determined.

It must be noted that due to incomplete records, there were missing values for many of the predictor variables. For example, only 3894 students out of the sample of 4170 had UGPA data in their files. This equates to 93.47%. The percentage of missing values for all of the other predictors are even lower. The majority of these missing values are attributable to the incomplete records of civilians and

foreign military students over whom AFIT exerts little control.

Table 2 provides descriptive statistics for all the non-indicator variables included in this sample. Appendix A displays frequency distributions for each of the non-indicator variables below. Appendix B provides descriptive statistics for each graduate program.

Table 2
Descriptive Statistics for Entire Sample

VARIABLE	# IN SAMPLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
GGPA	4168	3.52	0.36	0.00	4.00
UGPA	3894	3.05	0.40	1.90	4.00
GRET	2900	1203.24	141.07	670.00	1670.00
GREV	2900	535.60	91.59	200.00	870.00*
GREQ	2900	667.58	81.10	200.00	870.00*
GREA	1757	590.98	100.65	200.00	800.00
GMATV	722	31.53	6.06	5.00	48.00
GMATQ	722	32.66	6.46	11.00	54.00
GMATT	731	537.07	68.84	275.00	740.00
TOEFL	59	521.46	128.87	80.00	780.00

* Effective October 1, 1981, the maximum obtainable score on the GRE verbal, quantitative, and analytical aptitude tests was limited to 800. Prior to this, higher scores were possible, though rare.

Data Analysis

Guion states:

The validation of a selection instrument must deal with two questions, one concerning the evidence that a relationship exists between test and criterion, the other concerning the magnitude of that relationship (17: 158).

Thus, the first statistical procedure consisted of a correlational analysis. Correlation matrices containing all of the variables, both for the entire sample and broken down by program, were constructed.

Due to the fact that the AFIT registrar's office only has information on students who were selected for attendance and not on those who were not selected, the effects of restriction in range of the predictor variables must be considered. Therefore, the correlation coefficients from above were corrected for this phenomenon using the equation offered by Thorndike:

$$R = [r(y/x)]/[1-r^2+r^2(y/x)^2]^{1/2} \quad (3)$$

where x and y represent the predictor variable standard deviations for the restricted and unrestricted cases, respectively, and r and R represent the corresponding correlation coefficients (33: 173).

Prior to developing prediction models, however, it was necessary to break the sample into groups based upon the program in which the student studied. This separation is based on the conclusions reached by Madaus and Walsh. In their study, they found that due to different grading

practices between academic departments, the reliability of their criterion, GGPA, was unacceptably low. To correct for this, the authors formed groups based upon which program the student attended (24: 1109).

Regression techniques were used to build predictive models for each of the academic programs. These prediction models were in the form:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots \beta_n X_n \quad (3)$$

where Y is the dependent variable being predicted, X_i represents the predictor(s) and β_i is the weight associated with each predictor.

Initially, the predictive models chosen were those that exhibited the highest value for R^2 within each program. Since R^2 , the coefficient of determination, is a measure of the model's ability to explain the variability of the criterion variable, the higher this value, the better the predictive results of the model. These models were then tested for the aptness of each predictor within the model and the "goodness of fit" of the model itself. If the model didn't pass these tests, the model with the next highest value of R^2 was tested.

The test used to determine the aptness of each predictor used a test statistic in the form:

$$t = \beta_i / \text{standard error of } \beta_i \quad (4)$$

Since this statistic follows Student's t distribution, its

significance can be easily tested. If the value of t derived from this equation is statistically significant, the predictor significantly adds to the equation's ability to predict the criterion variable. Each predictor in the regression equation was tested and if its corresponding β was significant, the variable was determined to be useful in predicting GGPA.

The total model's ability to predict GGPA was analyzed through an analysis of variance (ANOVA). ANOVA is based on the fact that the total variability in the independent variable can actually be partitioned into two components as a result of the regression equation. These are the sum of squares due to regression (SSR) and the sum of squares of error (SSE). The larger SSR is relative to SSE, the better the prediction model fits the data. Since SSR can also be viewed as the portion of the variance in the independent variable that can be explained by the model and SSE as the unexplained variance, the larger the ratio, the more significant the model. All of the models produced above were also tested by this method.

Thus, the prediction models chosen to represent the data within each of the sorted groups was the model which best met these three criteria as described above.

In addition, no model was constructed which employed predictors from both the GRE and the GMAT. Since potential graduate students are likely to take either test, but not both, it seemed unproductive to construct models which

included both. Therefore, for some graduate programs, two prediction models were developed. One to predict GGPA if the student submits GRE scores and another for the prediction of GGPA with GMAT scores.

III. Results

Introduction

This chapter introduces the results of the statistical analyses described in Chapter II. The significant predictors of GCPA, separated by area of study, are presented. Only one prediction model is presented, however. The remainder of these models appear in appendix C.

Correlation Results

A correlation analysis was performed on the entire, non-sorted sample. The results of this procedure are summarized in Table 3. These correlation coefficients, corrected for restriction in range as described in the previous chapter, reinforce the notion of using standardized tests to aid in the selection of students for graduate school. As seen in Table 3, every aspect of both the GRE and the GMAT was significantly related to GGPA. In addition, UGPA was also significantly related to GGPA in the entire sample. Table 3 also reflects the prevalence of the GRE as the test of choice for potential graduate students regardless of their intended area of study. A total of 2900 of the 4170 students in the sample show GRE scores in their records while only 731 out of the same 4170 students received GMAT scores. Although this preference was expected from students in the School of Engineering with its focus on technical studies, the test of choice for students in the School of Systems and Logistics, with its focus on management, was also the GRE. Of the 722

that did take the GMAT, however, 607 were in the School of Systems and Logistics.

Table 3
Correlation of Predictors with GGPA for Entire Sample

<u>VARIABLE</u>	<u>CORRELATION</u>	<u>N</u>	<u>SIGNIFICANCE</u>
UGPA	0.1789	3894	<0.0001
GRET	0.3309	2900	<0.0001
GREV	0.2377	2900	<0.0001
GREQ	0.4021	2900	<0.0001
GREM	0.3895	1757	<0.0001
GMATV	0.4243	722	<0.0001
GMATQ	0.2563	722	<0.0001
GMATT	0.3272	731	<0.0001
TOEFL	0.1155	59	0.3836

Table 3 also reveals that TOEFL scores were the only predictors that were not significantly related with GGPA. This is not surprising as command of the English language is a necessary but not sufficient condition for successful graduate school performance. This fact, combined with the reality that if the TOEFL scores were exceptionally poor, the student would never have been accepted to graduate school in the first place, make the possibility of a significant relationship between TOEFL and GGPA highly unlikely.

The results in Table 3 also indicate that the predictors with the highest correlation with GGPA, when broken down by type of standardized test taken, are the GRE quantitative test and the GMAT verbal test. The appearance of GREQ and GMATV as the most significant predictors within their respective tests comes as no surprise. As mentioned previously, the majority of students with GMAT scores were in the School of Systems and Logistics. This school, with much of its curriculum consisting of courses in management, stresses the non-quantitative aspects of the Air Force. Therefore, those students with a strong background in the verbal skills (as those with high GMATV scores have), should be more successful than those lacking these skills. Similarly, the majority of those with GRE scores are in the School of Engineering (1923 out of 2900 total). In this school, the numerical ideas are highlighted and those students with strong backgrounds in the quantitative sciences will certainly be expected to excel.

As mentioned in the previous chapter, correlational matrices were also constructed after the sample had been sorted by area of study. A summary of these matrices is shown in Table 4. This table reflects only those predictor/criterion relationships which were significant at the 0.05 level. At this level, the probability of the relationship occurring as a result of chance are greatly reduced.

For those programs in the School of Engineering (the first 12 listed), one of the GRE tests were significantly correlated with GGPA in 11 of the 13 groups. In addition, UGPA was significant in 12 groups. In one program, Guidance Control, there were no significant predictors. The GMAT was only significant in one group.

In the School of Systems and Logistics, both the GRE and the GMAT were reliable predictors of GGPA. Here, the GRE was significant in 7 of the 9 programs and the GMAT highly correlated in 6. However, the usefulness of UGPA as a predictor was drastically less with significance in only 2 of the 9 groups.

Table 4
Significant Predictors for Each Program
Astronautical Engineering (N = 143)

VARIABLE	CORRELATION	N	SIGNIFICANCE
UGPA	0.2209	140	0.0087
GRET	0.6089	119	<0.0001
GREV	0.2844	119	0.0021
GREQ	0.8286	119	<0.0001
GREM	0.4350	55	0.0013

Table 4 (continued)

Aeronautical Engineering (N = 326)

<u>VARIABLE</u>	<u>CORRELATION</u>	<u>N</u>	<u>SIGNIFICANCE</u>
UGPA	0.2679	295	<0.0001
GREQ	0.4992	239	<0.0001
GREA	0.2553	134	0.0036

Computer Science (N = 308)

<u>VARIABLE</u>	<u>CORRELATION</u>	<u>N</u>	<u>SIGNIFICANCE</u>
UGPA	0.3137	286	<0.0001
GRET	0.5038	252	<0.0001
GREV	0.3556	252	<0.0001
GREQ	0.5534	252	<0.0001
GREA	0.5816	160	<0.0001

Table 4 (continued)
Electrical Engineering (N = 646)

VARIABLE	CORRELATION	N	SIGNIFICANCE
UGPA	0.3102	608	<0.0001
GRET	0.3034	482	<0.0001
GREV	0.1846	482	<0.0001
GREQ	0.4504	482	<0.0001
GREA	0.2984	344	<0.0001

Electro-Optical Engineering (N = 107)

VARIABLE	CORRELATION	N	SIGNIFICANCE
UGPA	0.3705	106	<0.0001
GRET	0.3328	72	0.0043
GREQ	0.5409	72	<0.0001

Engineering Physics (N = 166)

VARIABLE	CORRELATION	N	SIGNIFICANCE
UGPA	0.4207	153	<0.0001
GRET	0.2291	132	0.0084
GREV	0.2379	132	0.0067
GREQ	0.4322	132	<0.0001

Table 4 (continued)

Nuclear Engineering (N = 121)

VARIABLE	CORRELATION	N	SIGNIFICANCE
UGPA	0.3202	110	0.0007
GRET	0.5529	91	<0.0001
GREV	0.4828	91	<0.0001
GREQ	0.6621	91	<0.0001
GREA	0.5678	56	<0.0001

Operations Research (N = 213)

VARIABLE	CORRELATION	N	SIGNIFICANCE
UGPA	0.3241	192	<0.0001
GRET	0.3211	181	<0.0001
GREQ	0.5853	181	<0.0001
GREA	0.4126	118	<0.0001
GMATQ	0.7584	11	0.0078

Systems Engineering (N = 90)

VARIABLE	CORRELATION	N	SIGNIFICANCE
UGPA	0.1675	87	<0.0001
GRET	0.6958	63	<0.0001
GREV	0.5866	63	<0.0001
GREQ	0.7177	63	<0.0001
GREA	0.7066	40	<0.0001

Table 4 (continued)

Strategy and Tactics (N = 183)

<u>VARIABLE</u>	<u>CORRELATION</u>	<u>N</u>	<u>SIGNIFICANCE</u>
UGPA	0.3514	178	<0.0001
GRET	0.5365	154	<0.0001
GREV	0.3559	154	<0.0001
GREQ	0.6482	154	<0.0001
GREA	0.3477	76	0.0023

Space Operations (N = 134)

<u>VARIABLE</u>	<u>CORRELATION</u>	<u>N</u>	<u>SIGNIFICANCE</u>
UGPA	0.3724	129	<0.0001
GRET	0.4426	124	<0.0001
GREQ	0.5268	124	<0.0001
GREA	0.3729	124	<0.0001

Guidance Control (N = 21)

<u>VARIABLE</u>	<u>CORRELATION</u>	<u>N</u>	<u>SIGNIFICANCE</u>
-----------------	--------------------	----------	---------------------

No significant predictors for this program

Computer Engineering (N = 23)

<u>VARIABLE</u>	<u>CORRELATION</u>	<u>N</u>	<u>SIGNIFICANCE</u>
UGPA	0.4499	17	0.0407

Table 4 (continued)

Acquisition Logistics (N = 107)

<u>VARIABLE</u>	<u>CORRELATION</u>	<u>N</u>	<u>SIGNIFICANCE</u>
GMATQ	-0.3074	46	0.0377

Contracting Management (N = 168)

<u>VARIABLE</u>	<u>CORRELATION</u>	<u>N</u>	<u>SIGNIFICANCE</u>
GRET	0.3781	77	0.0016
GREV	0.4144	77	0.0003
GREA	0.5577	36	<0.0001
GMATV	0.3556	80	0.0019
GMATT	0.3071	80	0.0061

Engineering Management (N = 270)

<u>VARIABLE</u>	<u>CORRELATION</u>	<u>N</u>	<u>SIGNIFICANCE</u>
UGPA	0.2742	260	<0.0001
GRET	0.3003	201	<0.0001
GREQ	0.4576	201	<0.0001
GREA	0.5027	133	<0.0001
GMATQ	0.6115	60	0.0007
GMATT	0.3076	60	0.0174

Table 4 (continued)

Logistics Management (N = 544)

VARIABLE	CORRELATION	N	SIGNIFICANCE
UGPA	0.1714	474	0.0002
GRET	0.4334	298	<0.0001
GREV	0.3606	298	<0.0001
GREQ	0.4632	298	<0.0001
GREA	0.4986	127	<0.0001
GMATV	0.4545	181	<0.0001
GMATQ	0.4633	181	<0.0001
GMATT	0.4591	183	<0.0001

Maintenance Management (N = 91)

VARIABLE	CORRELATION	N	SIGNIFICANCE
GRET	0.7372	50	<0.0001
GREV	0.6936	50	<0.0001
GREQ	0.7203	50	<0.0001
GREA	0.7491	38	<0.0001

Table 4 (continued)

Systems Management (N = 300)

<u>VARIABLE</u>	<u>CORRELATION</u>	<u>N</u>	<u>SIGNIFICANCE</u>
GRET	0.5138	162	<0.0001
GREV	0.4486	162	<0.0001
GREQ	0.6041	162	<0.0001
GREM	0.5346	98	<0.0001
GMATV	0.5018	132	<0.0001
GMATQ	0.3853	132	<0.0001
GMATT	0.4430	133	<0.0001

Transportation Management (N = 54)

<u>VARIABLE</u>	<u>CORRELATION</u>	<u>N</u>	<u>SIGNIFICANCE</u>
-----------------	--------------------	----------	---------------------

No significant predictors for this program

Cost Analysis (N = 57)

<u>VARIABLE</u>	<u>CORRELATION</u>	<u>N</u>	<u>SIGNIFICANCE</u>
GRET	0.6958	24	<0.0001
GREQ	0.7630	24	<0.0001
GMATV	0.7885	33	<0.0001
GMATQ	0.5623	33	0.0015
GMATT	0.7535	33	<0.0001

Table 4 (continued)

Information Resources (N = 47)

VARIABLE	CORRELATION	N	SIGNIFICANCE
GRE A	0.5485	26	<0.0001
GRE Q	0.5266	30	<0.0001

Regression Results

Using the methodology described in the previous chapter, prediction models were constructed for all current graduate programs with significant predictors. These models are presented in Appendix C. In addition, two models were also developed based upon the results of the entire sample. Table 5 provides the result of this analysis.

The results in Appendix C indicate the usefulness of separating the sample by graduate program. The R^2 values of the models presented there range from a high of 0.9783 in the Astronautical Engineering program to a low of 0.2000 in the Acquisition Logistics program. Whereas the models produced from the non-sorted sample have R^2 values of 0.4279 and 0.4537, for the GRE and GMAT cases respectively, 16 of the 24 models produced from the sorted sample have higher values for this coefficient.

It is interesting to note that, in direct contrast to Bruno's study of predictors for graduate performance in the Army, these results indicate that the larger sample models have larger coefficients of determination than the smaller

sample models (DB: 37). The Information Resources program ($N = 47$, $R^2 = 0.2155$), the Computer Engineering program ($N = 21$, $R^2 = 0.2025$), and the Acquisition Logistics program ($N = 106$, $R^2 = 0.2000$) affirm this as their models exhibit the smallest coefficients and smallest N 's in this analysis.

Table 5

Prediction Models for GGPA

<u>VARIABLE</u>	<u>WEIGHT</u>	<u>SIGNIFICANCE</u>
INTERCEPT	3.8019	<0.0001
UGPA	0.0919	<0.0001
GMATT	-0.0137	<0.0001
GMATV	0.1243	<0.0001
GMATQ	0.0882	<0.0001

MODEL $R^2 = 0.4537$

<u>VARIABLE</u>	<u>WEIGHT</u>	<u>SIGNIFICANCE</u>
INTERCEPT	2.0650	<0.0001
UGPA	0.0932	<0.0001
GRET	-0.0106	<0.0001
GREQ	0.0117	<0.0001
GREV	0.0106	<0.0001
GREA	0.0007	<0.0001

MODEL $R^2 = 0.4279$

IV. Conclusions

Introduction

This chapter begins with a review of the research hypotheses from Chapter I. This section will focus on the supportability of each hypothesis based on the evidence presented in Chapter III. Immediately following is a discussion of the implications of these findings and the conclusions which may be drawn from them.

Hypothesis Review

The first research hypothesis stated that standardized tests, such as the GRE and GMAT, are valid predictors of AFIT graduate school performance. The results of this analysis certainly support this statement. When correlated over the entire sample, all the predictor/criterion relationships involving the GRE or GMAT were found to be significant beyond the 0.0001 level.

The second research hypothesis stated that undergraduate grade point averages are valid predictors of AFIT graduate school performance. Since the correlation of UGPA with GGPA, over the entire sample, yielded a coefficient which was also significant beyond the 0.0001 level, this assertion was supported.

The third research hypothesis stated that the correlations of the predictors and the criterion would vary between graduate degree programs. The results presented in

Table 4 support this claim. Although every predictor, with the exception of TOEFL, was significant beyond the 0.0001 level in the entire sample, none of the correlations performed within each program yielded similar results. In the correlations performed for the 22 programs, the number of significant predictors yielded for each program never exceeded six. In addition, two programs didn't have any significant predictors. Thus, the relationships between the predictors and the criterion varied significantly across AFIT programs.

The fourth research hypothesis stated that the significant predictors of each program could be combined into predictive models which produce significant results was also supported. The predictive models presented in Table 7 are all significant beyond the 0.0001 level.

Discussion

The results presented in Table 6 are actually a summary of the number of programs in which each predictor is valid. In an effort to visualize trends in the data, this table has differentiated between the nine programs in the School of Systems and Logistics and the 13 programs in the School of Engineering.

Based on the results presented in Table 6, it is interesting to note that UGPA is a significant predictor in twelve of the 13 School of Engineering programs. In addition, in the program where UGPA is not a significant

predictor, Guidance Control (N = 21), the average UGPA (2.94) in this group is the lowest in the Engineering School. Combined with the facts that in this Guidance Control group, the average GRE^T score (1269.28) is the second highest in the School of Engineering and the average GGPA (3.56) was above the sample average, an idea of the possible bias inherent to grade point averages can be seen. Based on the average GRE^T score and average GGPA in this group, it would seem that these students are not as poor as their average UGPA would indicate. Since undergraduate grade point averages differ significantly across undergraduate institutions, with some being very lenient and others being very strict, it is not difficult to see how this bias, combined with a small sample size, can reduce the effectiveness of UGPA as a predictor.

The Guidance Control program aside, it can be seen from Table 6 that not only is UGPA a valid predictor within the School of Engineering but also it is a poor predictor within the School of Systems and Logistics. A possible explanation for this phenomenon may lie in the fact that students who traditionally enter the School of Engineering have already studied engineering as undergraduates. Thus, their undergraduate grade point averages reflect their academic success in an area similar to their intended area of graduate study. On the other hand, students who enter the School of Systems and Logistics rarely have studied the art of management as an undergraduate (due to the Air Force's desire for potential officers with technical degrees) and therefore,

their undergraduate grade point averages reflect their academic success in an area unrelated to their intended area of graduate work. Although thus unfamiliarity with their intended area of study does not preclude them from being successful students, it does reduce the effectiveness of their undergraduate grade point averages as predictors of their graduate performance.

Table 6
Summary of Number of Programs (By School) in
which the Predictor is Significant

Predictor	School of Systems and Logistics	School of Engineering
UGPA	2	12
GRET	6	10
GREV	4	7
GREQ	6	11
GREA	6	9
GMATV	4	0
GMATQ	5	1
GMATT	5	0
TOEFL	0	0

Table 6 also demonstrates the validity of using the GMAT to predict graduate grades in the School of Systems and Logistics. Since the GMAT is designed to assess the qualifications of potential students for study in business or

management, its validity in the School of Systems and Logistics, as well as its poor predictive effectiveness in the School of Engineering, come as no surprise.

The findings of this study are deeper than just generalities, however. The preceding analysis has demonstrated that in AFIT, different predictors are needed for different academic programs. Although either common sense or intuition may suggest that the GRE is a more appropriate predictor for the School of Engineering programs, and similarly the GMAT for the School of Systems and Logistics programs, this analysis has shown that the difference is much more specific than this. For example, although GREA is a very significant predictor for the Electrical Engineering program, it is not a significant predictor for the Engineering Physics program. This finding implies that the skills required to excel in each program may differ, even within the same school (i.e. Engineering vs. Management). Since different skills may be required, it requires different tests to measure those skills. Therefore, a test which measures analytic ability (as the GREA does) tends to predict performance better in a program like Electrical Engineering, which may require more analytic skills than another program.

Instead of asking the AFIT Admissions office to assume which skills are needed in a particular program, and then to find a test to measure those skills, the table of significant predictors enables the selection committee to see which tests

are significantly related to academic performance, by program. Thus, the Admissions office can select students based on the most appropriate criteria. In addition, the predictive models enable the selection committee to use the students' scores, on these predictors, to forecast his or her graduate performance. This eliminates the requirement for cut-off values of any test which may eliminate an otherwise potentially successful student.

Conclusions

This study has shown that the AFIT Registrar's office is using valid predictors for the selection of students to attend graduate school. However, this study has also shown that the application of all these predictors is not appropriate for every AFIT graduate program. More specifically, AFIT should not use the same predictors for each program. Comparisons of the relationships between predictors and criterion, by program, have revealed significant differences in the predictive ability of the same variables. These predictors should be applied on a program by program basis as indicated in Table 4. The methodology for applying these predictors should be consistent with the predictive models presented in Appendix C.

While validating the use of the present predictors of academic performance, this study does not preclude the existence of other, more powerful predictors. However, before money and effort are expended in the search for these

predictors, a look at the marginal returns possible as a result of these new variables should be considered. A look at the graduation rates for the last three years of this study reveals that only 9 of the 1211 total students were voluntarily or involuntarily dismissed from AFIT for academic deficiency. This represents a 0.77% failure rate. Of course, this figure does not take into account those students who did not graduate at the expected time. These students are generally those who have not completed their theses requirements on schedule. Even though all course work may be complete, these students do not graduate until their thesis is finished. For the most part, this phenomenon indicates, not a lack of academic ability, but a lack of motivation. Unfortunately, variables indicating the presence or absence of motivation are not considered in the selection process.

With this low failure rate in mind, a search for new predictors should have as its goal differentiating among qualified students, thus determining which are better suited for AFIT, as opposed to the broader task of separating the qualified students from the unqualified ones.

Suggestions for Future Research

Additional research should be conducted in the future to eliminate the effects that small sample size may have had within certain programs. For example, the Guidance Control program had a sample size of only 21 students. Further research should be conducted after more students have entered the program so that results with more confidence may be

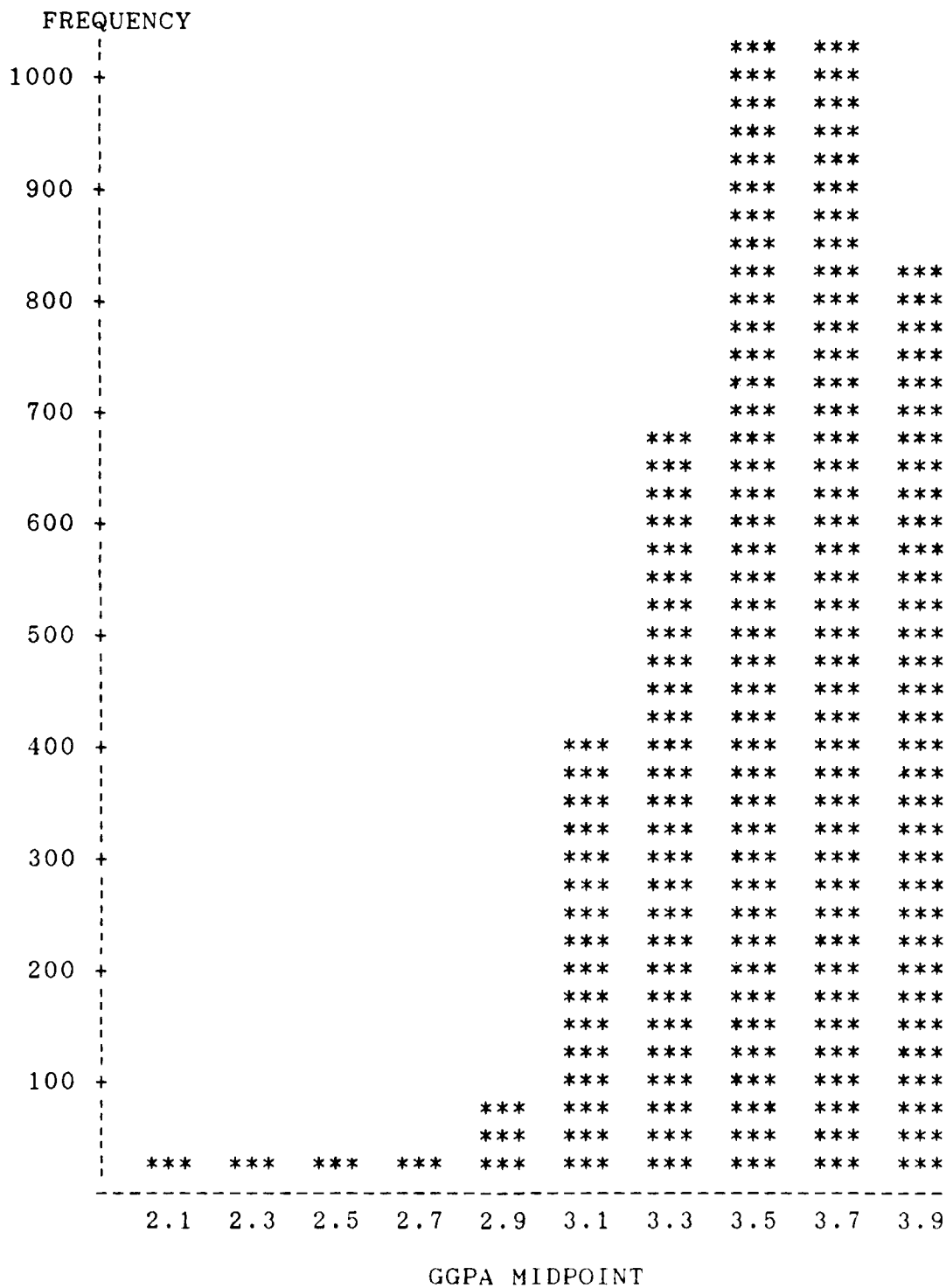
obtained. In addition, since only 59 students reported scores on the TOEFL, these results may also need to be reconsidered after the sample size has increased.

Summary

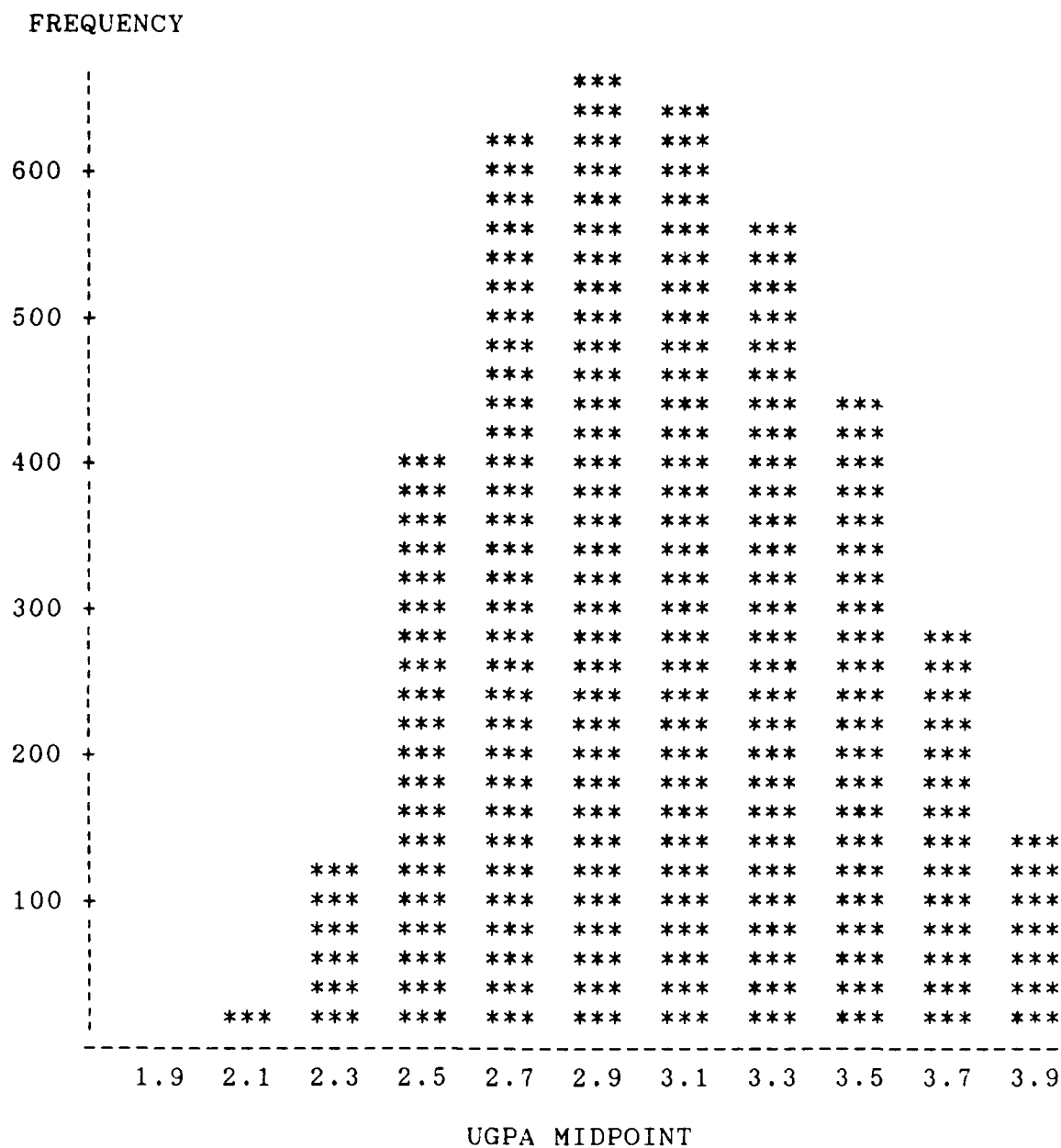
In summary, this thesis has demonstrated that selection to AFIT should be conducted on a program by program basis. Although the overall content of the engineering and management disciplines is quite different, they also exhibit little homogeneity within themselves. Thus, instead of using a single set of predictors for all AFIT students, or even two sets with one for each school, a different set of predictors should be used for each program. The selection committee certainly recognizes that astronautical engineering has little in common with logistics management. By the same token however, the committee should also recognize that astronautical engineering has little in common with electrical engineering and, therefore, should use different predictors of academic success for each program.

Appendix A: Frequency Distributions for
Criterion and Predictor Variables

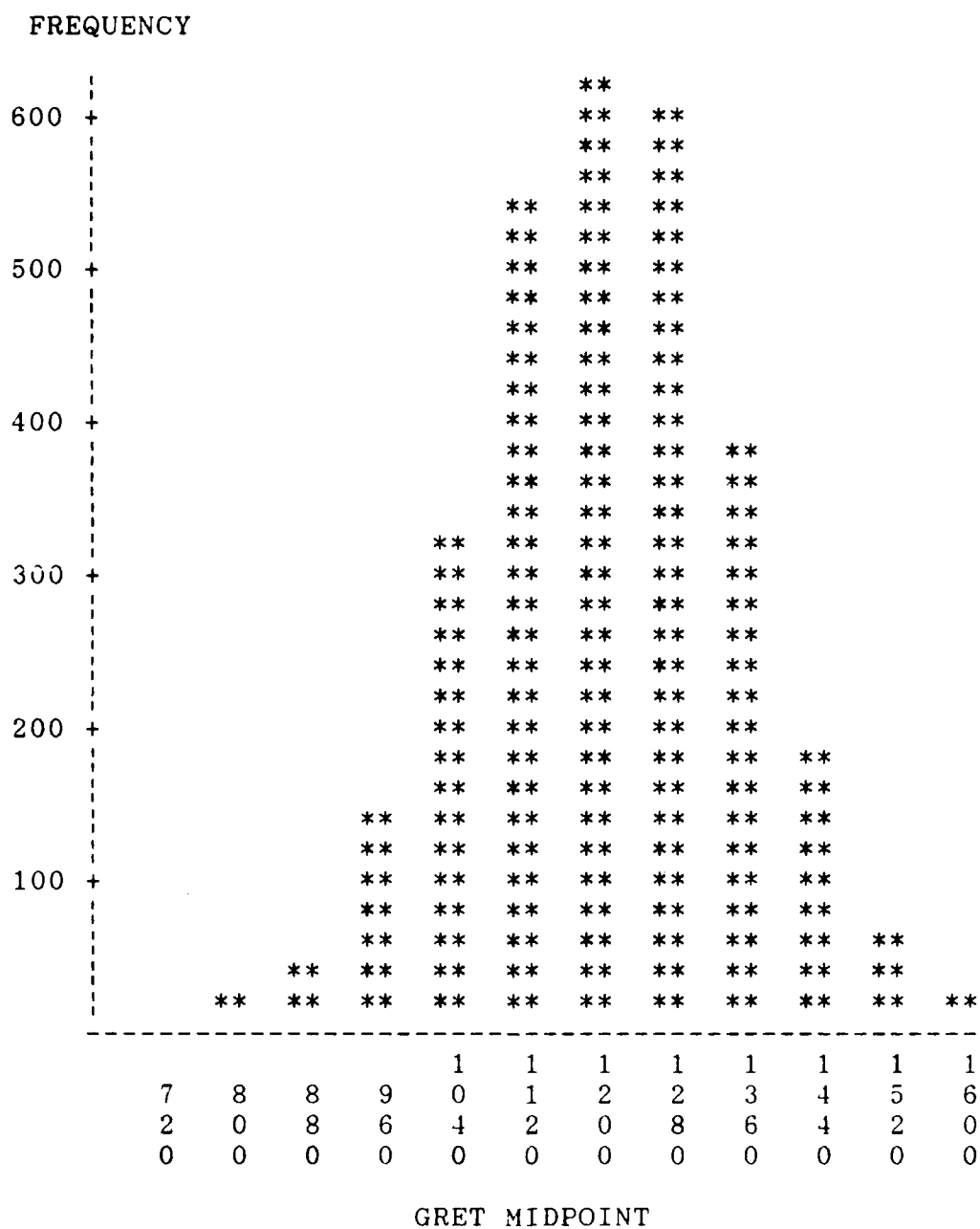
AFIT Graduate Grade Point
Average Distribution (1977 - 1987)



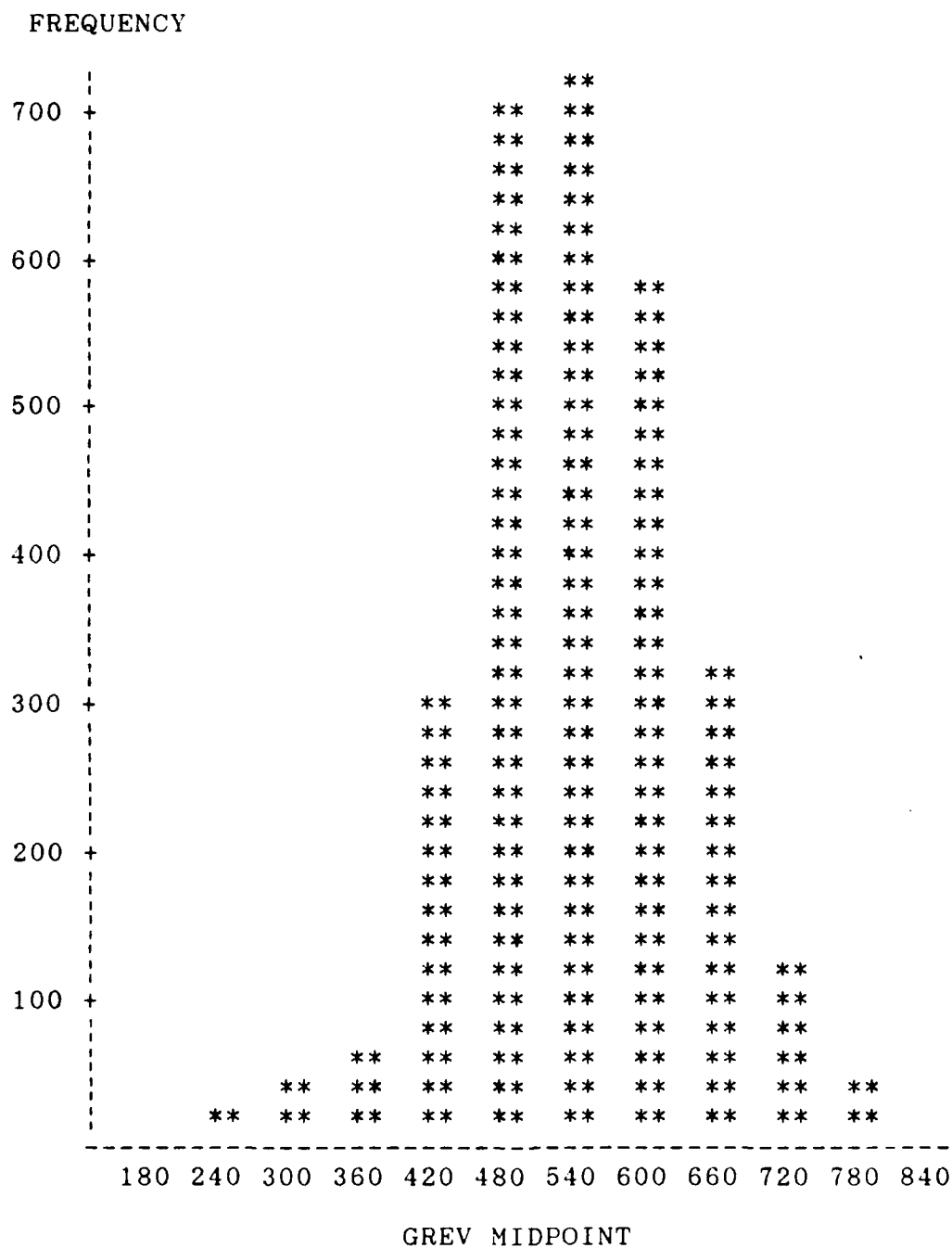
AFIT Undergraduate Grade Point
Average Distribution (1977 - 1987)



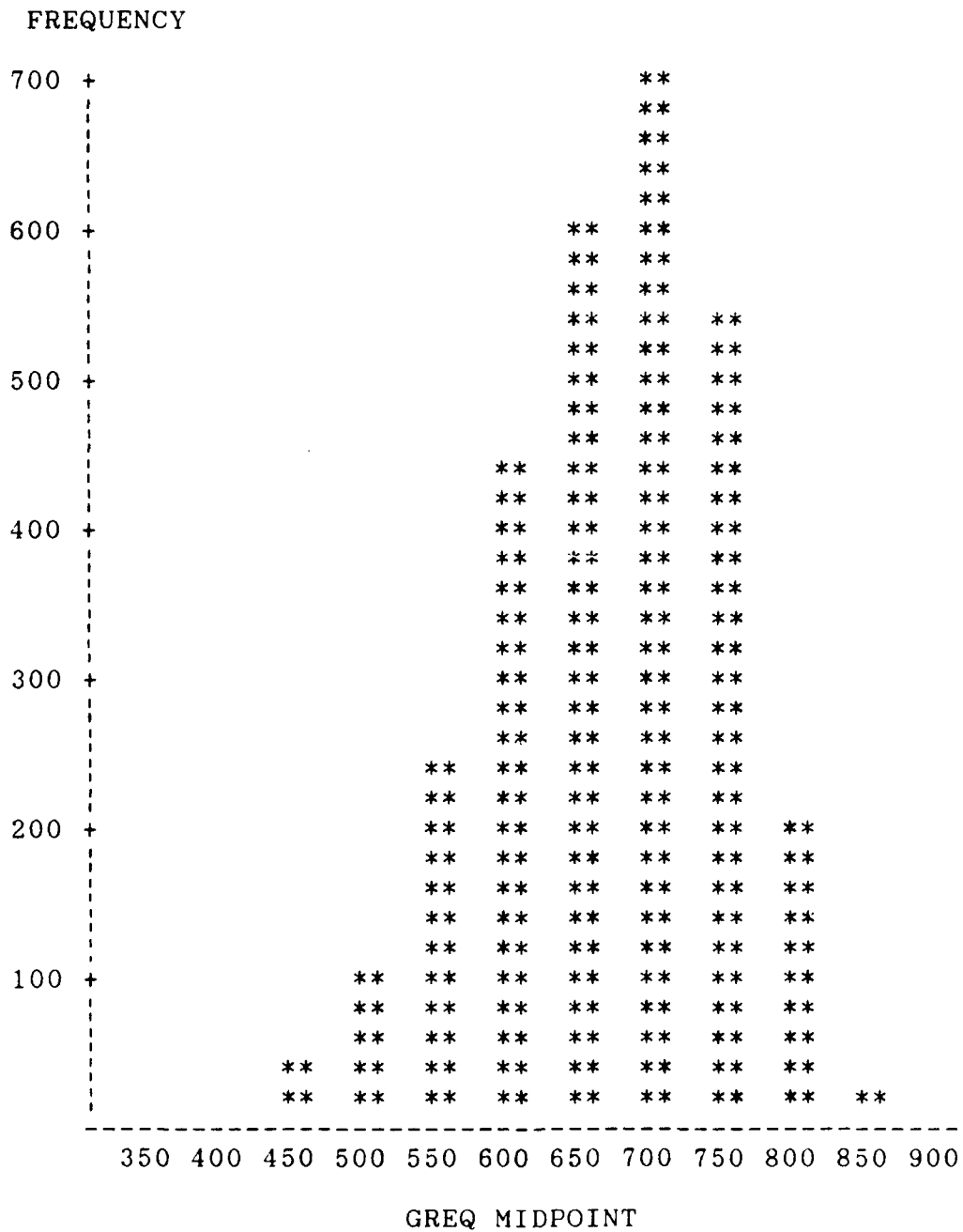
AFIT GRET Score Distribution (1977 - 1987)



AFIT GREV Score Distribution (1977 - 1987)

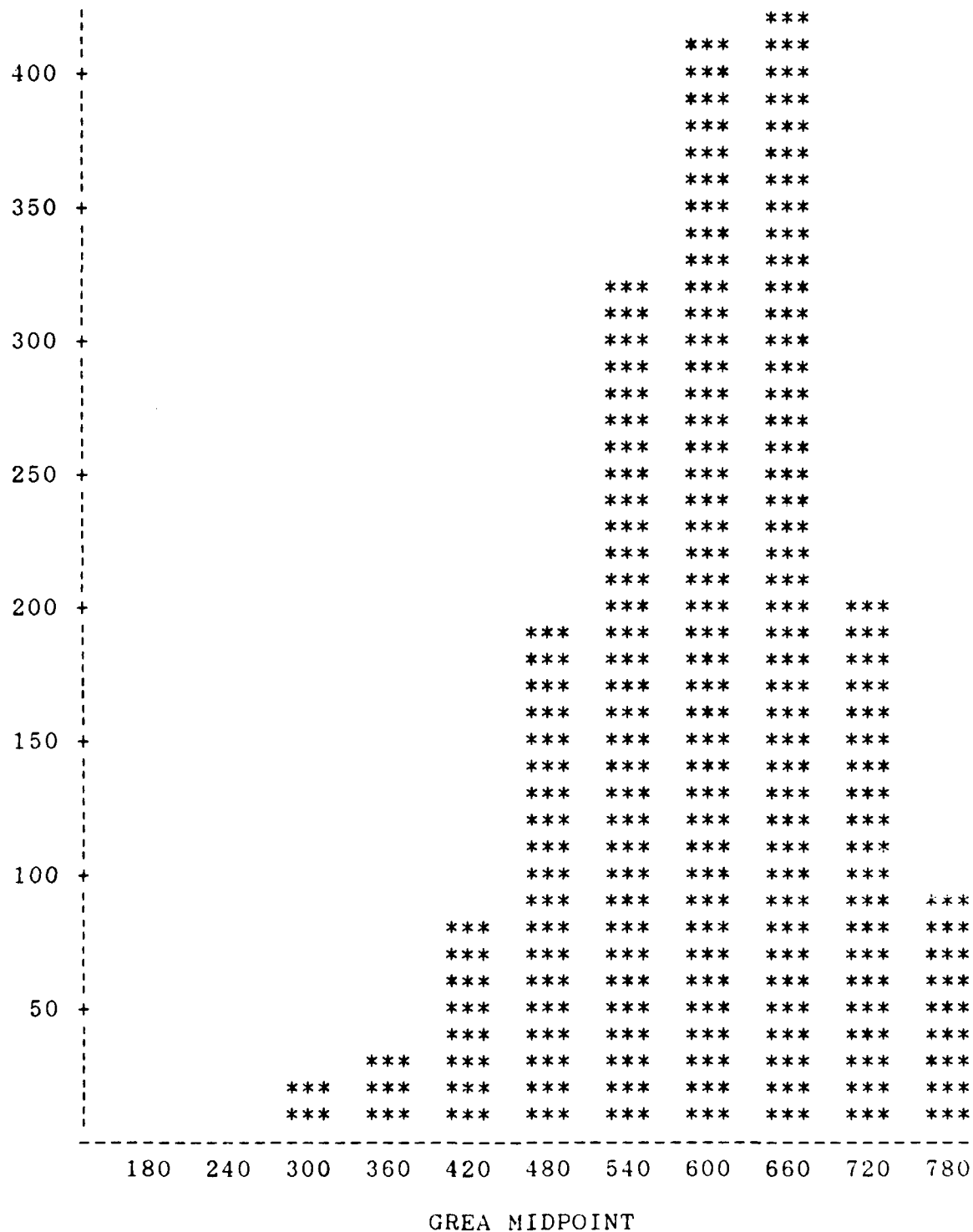


AFIT GREQ Score Distribution (1977 - 1987)

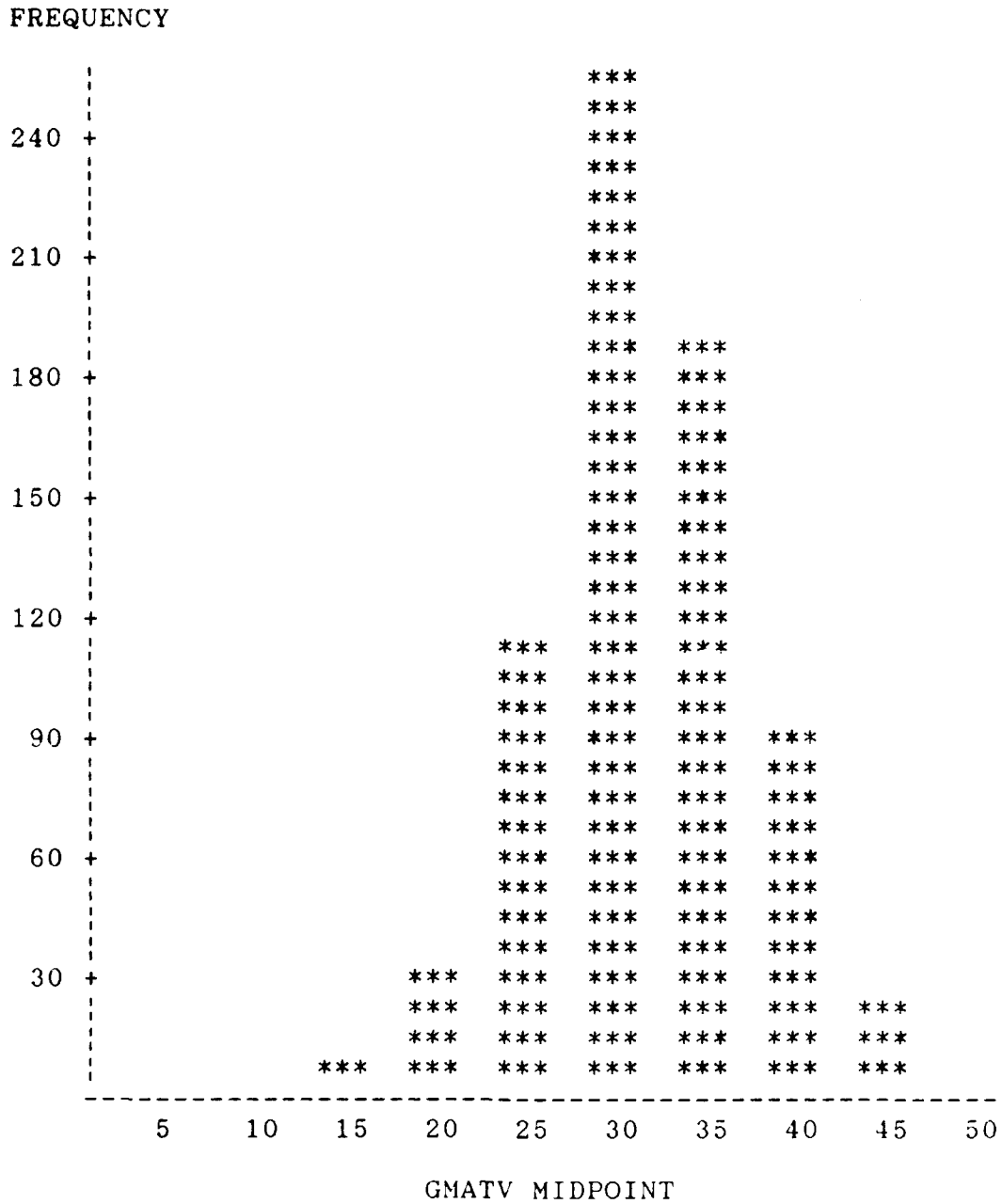


AFIT GREA Score Distribution (1977 - 1987)

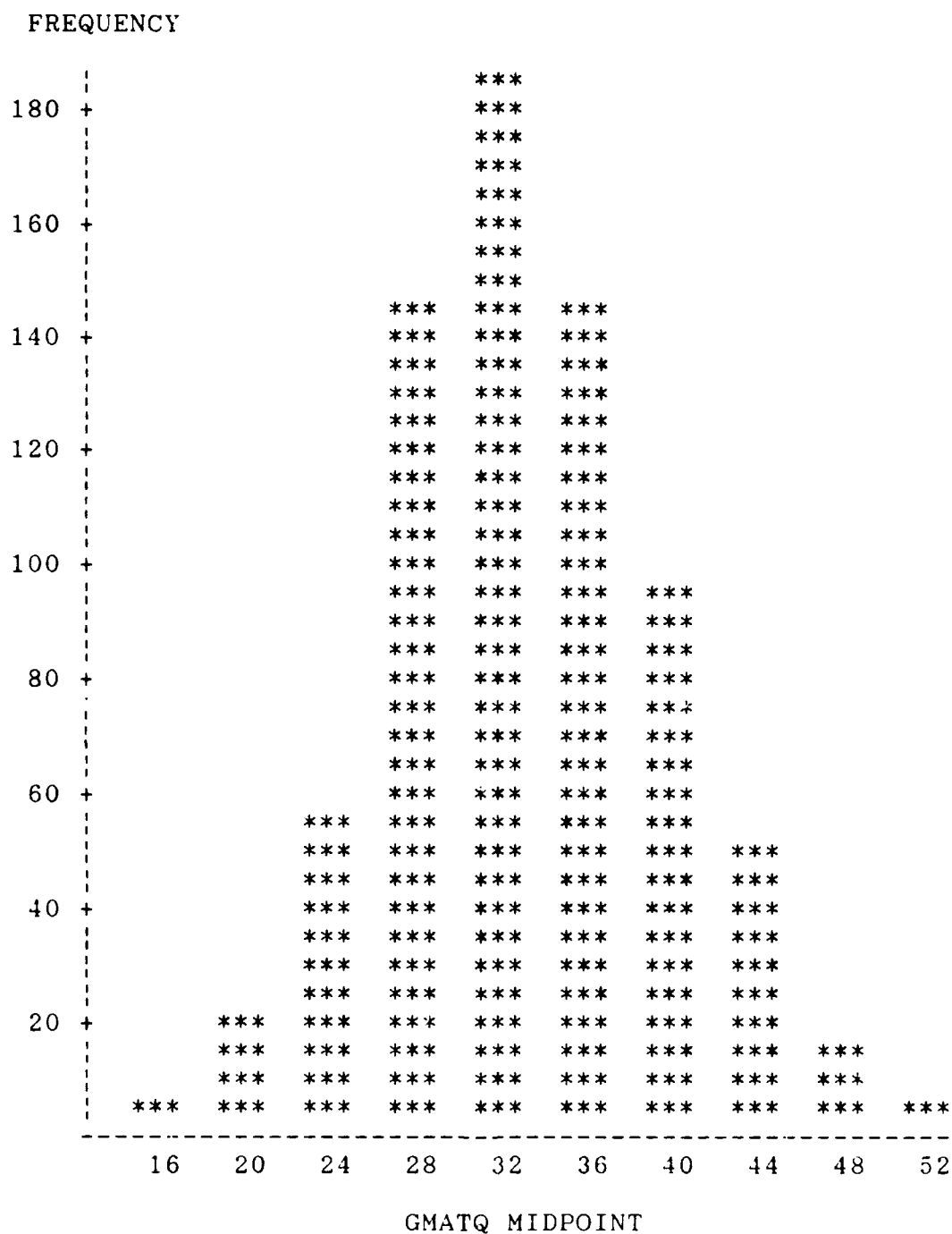
FREQUENCY



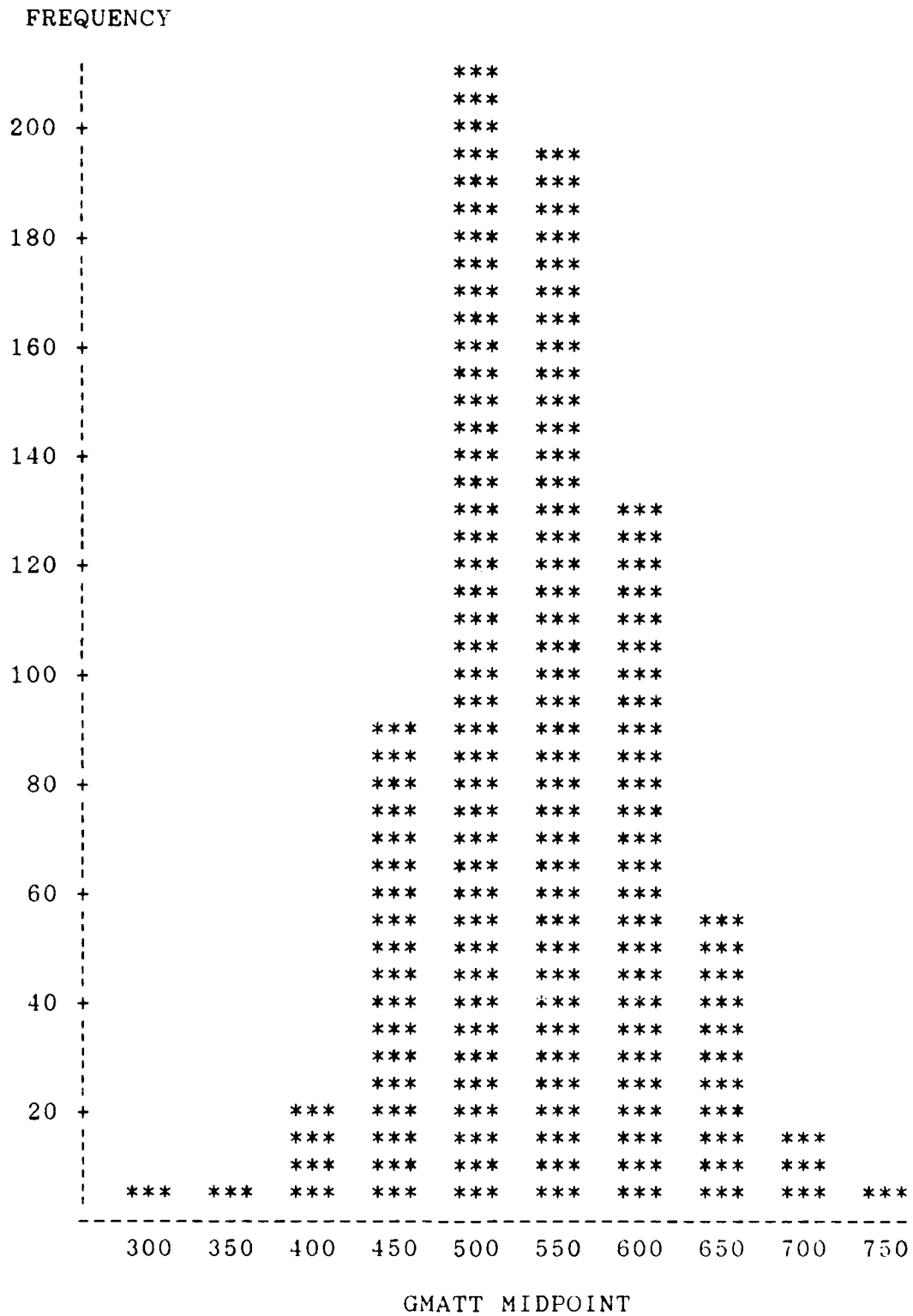
AFIT GMATV Score Distribution (1977 - 1987)



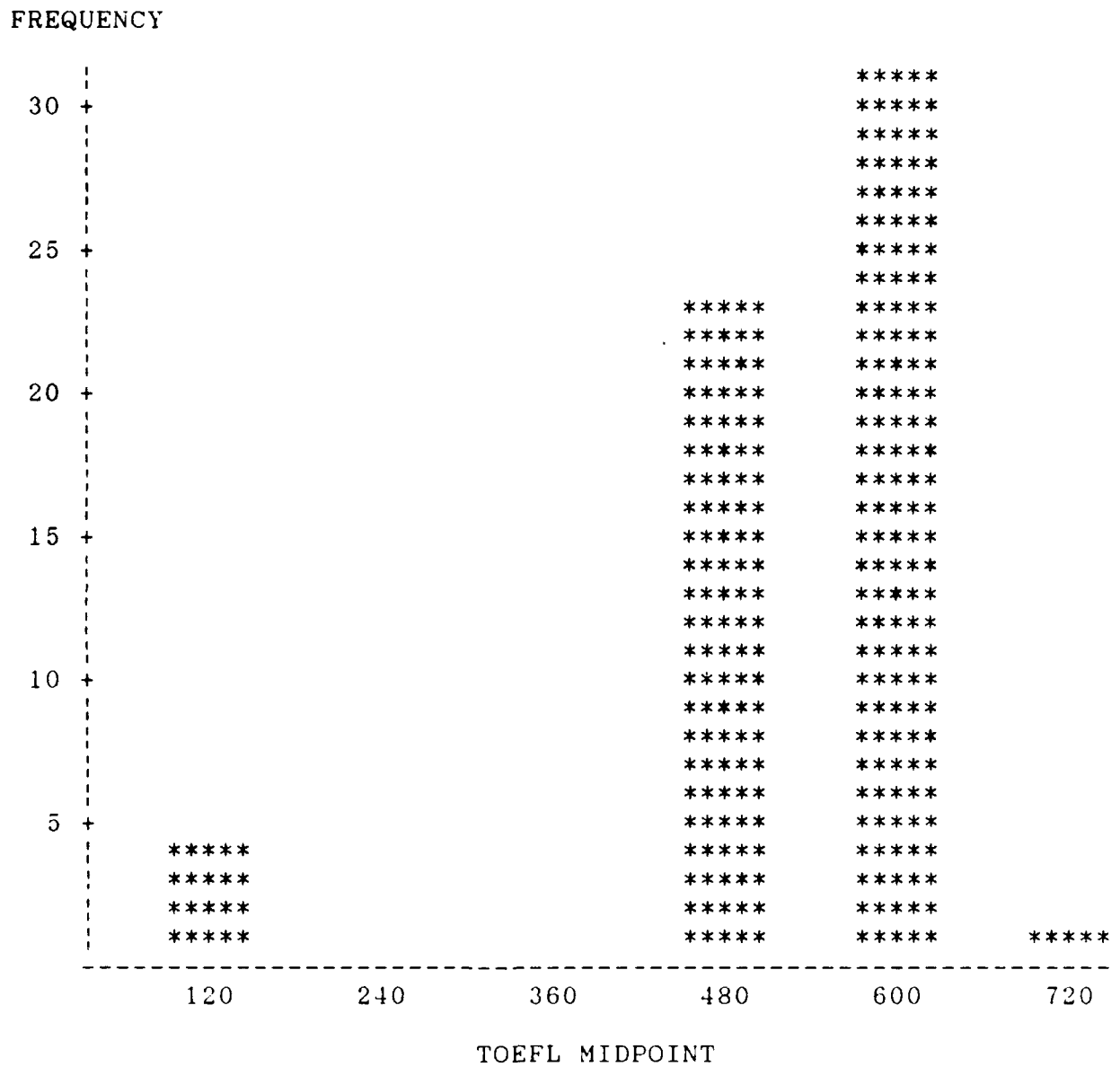
AFIT GMATQ Score Distribution (1977 - 1987)



AFIT GMATT Score Distribution (1977 - 1987)



AFIT TOEFL Score Distribution (1977 - 1987)



Appendix B: Descriptive Statistics for
Criterion and Predictor Variables
By Program

Descriptive Statistics for the
Aeronautical Engineering Program

VARIABLE	# IN SAMPLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
GGPA	326	3.37	0.35	1.77	4.00
UGPA	295	3.10	0.38	2.19	4.00
GRET	239	1204.76	127.06	790.00	1500.00
GREV	239	521.08	90.52	260.00	750.00
GREQ	239	681.68	67.69	490.00	850.00
GREA	134	607.68	100.36	300.00	800.00
GMATV	11	33.00	5.54	25.00	41.00
GMATQ	11	34.27	6.23	24.00	47.00
GMATT	11	557.63	62.19	491.00	690.00
TOEFL	10	561.60	56.71	452.00	633.00

Descriptive Statistics for the
Astronautical Engineering Program

VARIABLE	# IN SAMPLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
GGPA	143	3.43	0.35	1.75	4.00
UGPA	140	3.15	0.45	2.30	3.88
GRET	119	1254.53	107.02	1000.00	1480.00
GREV	119	540.58	83.67	360.00	750.00
GREQ	119	715.12	55.12	580.00	820.00
GREA	55	595.81	90.48	360.00	780.00
GMATV	4	32.00	4.83	25.00	36.00
GMATQ	4	37.25	1.70	35.00	39.00
GMATT	4	543.75	37.37	507.00	582.00
TOEFL	0				

Descriptive Statistics for the
Computer Science Program

VARIABLE	# IN SAMPLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
GGPA	308	3.56	0.34	1.07	4.00
UGPA	286	3.13	0.37	2.18	4.00
GRET	252	1208.76	150.62	800.00	1510.00
GREV	252	536.86	98.00	230.00	760.00
GREQ	252	672.02	87.75	410.00	820.00
GREA	160	602.00	104.80	200.00	800.00
GMATV	16	31.93	7.34	19.00	44.00
GMATQ	16	35.87	5.01	26.00	46.00
GMATT	16	561.50	62.71	446.00	667.00
TOEFL	7	539.14	47.02	480.00	610.00

Descriptive Statistics for the
Electrical Engineering Program

VARIABLE	# IN SAMPLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
GGPA	646	3.46	0.35	1.48	4.00
UGPA	608	3.13	0.39	2.11	4.00
GRET	482	1213.83	138.85	750.00	1580.00
GREV	482	535.14	92.36	200.00	800.00
GREQ	482	678.17	73.01	470.00	820.00
GREA	344	594.97	101.52	260.00	800.00
GMATV	19	31.79	4.95	24.00	41.00
GMATQ	19	37.00	5.48	27.00	46.00
GMATT	20	563.10	62.02	460.00	683.00
TOEFL	6	605.33	99.36	513.00	780.00

Descriptive Statistics for the
Electro-Optical Engineering Program

VARIABLE	# IN SAMPLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
GGPA	107	3.44	0.33	2.21	4.00
UGPA	106	3.23	0.40	2.38	3.94
GRET	72	1238.19	139.14	930.00	1580.00
GREV	72	540.97	93.37	360.00	790.00
GREQ	72	698.61	72.19	520.00	810.00
GREA	49	609.38	89.24	420.00	790.00
GMATV	3	33.66	1.15	33.00	35.00
GMATQ	3	37.66	4.16	33.00	41.00
GMATT	3	585.00	34.77	548.00	560.00
TOEFL	1	560.00			

Descriptive Statistics for the
Engineering Physics Program

VARIABLE	# IN SAMPLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
GGPA	166	3.35	0.45	0.93	4.00
UGPA	153	3.14	0.42	2.05	3.96
GRET	132	1256.38	140.47	920.00	1670.00
GREV	132	561.74	100.24	300.00	870.00
GREQ	132	693.03	66.04	500.00	870.00
GREA	77	610.52	93.66	280.00	800.00
GMATV	4	34.50	7.54	29.00	45.00
GMATQ	4	36.75	11.64	20.00	47.00
GMATT	4	586.25	121.61	435.00	730.00
TOEFL	2	515.00	21.21	500.00	530.00

Descriptive Statistics for the
Nuclear Engineering Program

VARIABLE	# IN SAMPLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
GGPA	121	3.39	0.43	1.18	4.00
UGPA	110	3.10	0.36	2.35	3.96
GRET	91	1251.31	147.46	900.00	1570.00
GREV	91	566.26	91.74	360.00	780.00
GREQ	91	683.84	77.79	500.00	830.00
GREA	56	611.07	86.01	400.00	780.00
GMATV	3	32.33	1.15	31.00	33.00
GMATQ	3	38.66	2.08	37.00	41.00
GMATT	3	580.67	16.77	570.00	600.00
TOEFL	0				

Descriptive Statistics for the
Operations Research Program

VARIABLE	# IN SAMPLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
GGPA	213	3.59	0.27	2.44	4.00
UGPA	192	3.19	0.37	2.20	4.00
GRET	181	1212.20	137.28	760.00	1530.00
GREV	181	520.44	98.27	200.00	770.00
GREQ	181	692.54	70.94	470.00	870.00
GREA	118	592.54	107.85	220.00	800.00
GMATV	11	34.45	5.94	27.00	43.00
GMATQ	11	36.54	5.76	29.00	44.00
GMATT	11	582.63	74.11	500.00	710.00
TOEFL	11	538.36	21.45	493.00	573.00

Descriptive Statistics for the
Systems Engineering Program

VARIABLE	# IN SAMPLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
GGPA	90	3.39	0.44	1.73	4.00
UGPA	87	3.12	0.35	2.26	3.86
GRET	63	1201.90	148.68	920.00	1650.00
GREV	63	526.98	91.55	360.00	840.00
GREQ	63	671.26	90.54	350.00	830.00
GREA	40	596.25	118.89	280.00	780.00
GMATV	4	30.25	5.37	24.00	37.00
GMATQ	4	38.00	4.83	31.00	42.00
GMATT	4	563.00	65.14	475.00	631.00
TOEFL	0				

Descriptive Statistics for the
Strategy and Tactics Program

VARIABLE	# IN SAMPLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
GGPA	183	3.56	0.24	2.75	4.00
UGPA	178	3.01	0.36	2.16	3.90
GRET	154	1250.06	131.64	760.00	1570.00
GREV	154	562.59	93.47	310.00	790.00
GREQ	154	686.68	70.96	450.00	830.00
GREA	76	613.02	92.56	400.00	790.00
GMATV	21	35.61	4.52	26.00	48.00
GMATQ	21	37.19	5.20	26.00	47.00
GMATT	22	596.18	48.23	522.00	696.00
TOEFL	0				

Descriptive Statistics for the
Space Operations Program

VARIABLE	# IN SAMPLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
GGPA	134	3.56	0.29	1.59	3.98
UGPA	129	3.08	0.34	2.19	3.91
GRET	124	1230.64	113.50	970.00	1580.00
GREV	124	544.19	77.17	410.00	800.00
GREQ	124	677.98	68.71	510.00	810.00
GREA	77	610.38	81.87	410.00	800.00
GMATV	5	32.80	5.11	25.00	39.00
GMATQ	5	34.00	5.87	29.00	44.00
GMATT	6	568.50	68.11	476.00	658.00
TOEFL	0				

Descriptive Statistics for the
Guidance Control Program

VARIABLE	# IN SAMPLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
GGPA	21	3.56	0.25	2.96	4.00
UGPA	17	2.94	0.37	2.30	3.71
GRET	14	1269.28	83.89	1090.00	1370.00
GREV	14	540.71	62.19	440.00	640.00
GREQ	14	728.57	49.12	620.00	810.00
GREA	0				
GMATV	1	36.00			
GMATQ	1	41.00			
GMATT	2	623.50	2.12	622.00	625.00
TOEFL	0				

Descriptive Statistics for the
Computer Engineering Program

VARIABLE	# IN SAMPLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
GGPA	22	3.66	0.23	3.01	3.90
UGPA	21	3.30	0.30	2.59	3.71
GRET	22	1284.09	117.74	1020.00	1500.00
GREV	22	584.54	83.99	410.00	710.00
GREQ	22	700.00	53.09	620.00	790.00
GREA	21	647.62	97.31	410.00	800.00
GMATV	0				
GMATQ	0				
GMATT	0				
TOEFL	0				

Descriptive Statistics for the
Acquisition Logistics Program

VARIABLE	# IN SAMPLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
GGPA	107	3.57	0.27	2.62	4.00
UGPA	99	2.98	0.44	2.10	3.96
GRET	52	1179.04	119.88	910.00	1460.00
GREV	52	552.30	74.00	410.00	710.00
GREQ	52	626.53	74.69	460.00	800.00
GREM	33	578.63	89.75	400.00	750.00
GMATV	46	32.54	5.39	21.00	43.00
GMATQ	46	32.17	6.86	19.00	50.00
GMATT	47	540.46	59.78	408.00	647.00
TOEFL	0				

Descriptive Statistics for the
Contracting Management Program

VARIABLE	# IN SAMPLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
GGPA	168	3.63	0.24	2.76	4.00
UGPA	160	2.96	0.45	1.90	4.00
GRET	77	1168.70	138.64	870.00	1530.00
GREV	77	549.09	83.77	410.00	760.00
GREQ	77	620.90	81.13	450.00	770.00
GREM	36	571.66	85.84	360.00	780.00
GMATV	80	31.60	5.22	19.00	44.00
GMATQ	80	29.98	5.74	18.00	45.00
GMATT	80	520.66	60.52	381.00	650.00
TOEFL	1	480.00			

Descriptive Statistics for the
Engineering Management Program

VARIABLE	# IN SAMPLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
GGPA	270	3.61	0.24	2.98	4.00
UGPA	260	2.86	0.39	1.96	3.92
GRET	201	1173.03	119.57	900.00	1490.00
GREV	201	512.83	75.90	310.00	730.00
GREQ	201	660.69	73.27	480.00	820.00
GREA	133	571.35	90.60	320.00	800.00
GMATV	60	30.03	6.39	14.00	43.00
GMATQ	60	32.76	5.93	16.00	47.00
GMATT	60	524.70	71.51	310.00	670.00
TOEFL	2	94.00	2.82	92.00	96.00

Descriptive Statistics for the
International Logistics Program

VARIABLE	# IN SAMPLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
GGPA	47	3.53	0.24	3.05	4.00
UGPA	45	2.93	0.41	2.23	3.82
GRET	26	1150.38	140.04	970.00	1530.00
GREV	26	532.69	89.91	440.00	770.00
GREQ	26	615.00	75.96	490.00	800.00
GREA	16	539.37	74.42	430.00	680.00
GMATV	17	28.64	7.76	9.00	41.00
GMATQ	17	30.35	9.42	14.00	54.00
GMATT	18	501.66	99.75	275.00	670.00
TOEFL	0				

Descriptive Statistics for the
Logistics Management Program

VARIABLE	# IN SAMPLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
GGPA	544	3.55	0.43	0.00	4.00
UGPA	474	2.93	0.42	2.06	3.96
GRET	298	1132.75	152.35	670.00	1560.00
GREV	298	518.12	97.88	200.00	770.00
GREQ	298	615.53	88.86	340.00	850.00
GREA	127	539.21	122.72	230.00	800.00
GMATV	181	31.41	5.71	5.00	46.00
GMATQ	181	31.53	5.81	15.00	48.00
GMATT	47	478.76	180.71	90.00	637.00
TOEFL	0				

Descriptive Statistics for the
Maintenance Management Program

VARIABLE	# IN SAMPLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
GGPA	91	3.60	0.23	3.01	3.98
UGPA	90	2.97	0.41	2.01	3.96
GRET	50	1133.80	137.86	840.00	1410.00
GREV	50	525.09	79.59	410.00	720.00
GREQ	50	604.80	86.69	420.00	810.00
GREA	38	574.73	87.11	400.00	730.00
GMATV	31	30.61	5.41	19.00	44.00
GMATQ	31	28.77	6.33	11.00	45.00
GMATT	31	508.90	65.59	312.00	670.00
TOEFL	0				

Descriptive Statistics for the
Systems Management Program

VARIABLE	# IN SAMPLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
GGPA	300	3.53	0.43	0.75	4.00
UGPA	288	2.93	0.38	2.20	4.00
GRET	162	1198.14	140.56	680.00	1480.00
GREV	162	540.43	85.88	300.00	700.00
GREQ	162	660.96	76.00	380.00	800.00
GREA	98	584.48	99.88	290.00	760.00
GMATV	132	31.53	7.35	10.00	46.00
GMATQ	132	35.11	5.92	20.00	53.00
GMATT	133	551.45	76.21	371.00	740.00
TOEFL	6	556.66	47.31	510.00	637.00

Descriptive Statistics for the
Transportation Management Program

VARIABLE	# IN SAMPLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
GGPA	54	3.58	0.32	2.50	4.00
UGPA	54	3.05	0.36	2.44	3.73
GRET	33	1140.60	136.35	910.00	1390.00
GREV	33	544.84	76.40	390.00	710.00
GREQ	33	595.75	96.11	430.00	830.00
GREA	26	546.92	82.25	400.00	670.00
GMATV	17	30.47	5.87	19.00	43.00
GMATQ	17	26.47	6.23	11.00	37.00
GMATT	17	490.76	70.40	312.00	590.00
TOEFL	0				

Descriptive Statistics for the
Cost Analysis Program

VARIABLE	# IN SAMPLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
GGPA	57	3.58	0.28	2.42	4.00
UGPA	53	2.93	0.42	2.13	3.88
GRET	24	1144.58	117.43	930.00	1350.00
GREV	24	490.41	52.12	420.00	630.00
GREQ	24	654.16	84.38	490.00	750.00
GREA	16	576.87	59.18	460.00	670.00
GMATV	33	31.09	5.36	21.00	45.00
GMATQ	33	33.96	5.95	22.00	45.00
GMATT	33	543.09	60.23	430.00	670.00
TOEFL	0				

Descriptive Statistics for the
Information Resources Program

VARIABLE	# IN SAMPLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
GGPA	48	3.64	0.21	3.09	4.00
UGPA	47	3.03	0.39	2.29	3.75
GRET	30	1156.00	150.23	880.00	1450.00
GREV	30	551.33	93.24	390.00	780.00
GREQ	30	601.33	81.14	460.00	780.00
GREA	26	586.53	82.55	480.00	770.00
GMATV	23	31.21	5.17	22.00	45.00
GMATQ	23	29.78	5.35	21.00	40.00
GMATT	23	518.52	44.71	432.00	610.00
TOEFL	0				

Appendix C: Multiple Regression Prediction Models

Regression Model for the
Astronautical Engineering Program

<u>VARIABLE</u>	<u>WEIGHT</u>	<u>SIGNIFICANCE</u>
INTERCEPT	-1.5419	<0.0001
UGPA	0.1152	<0.0001
GRET	-0.0190	<0.0001
GREQ	0.0276	<0.0001
GREM	-0.0051	<0.0001
GREV	0.0218	<0.0001

SAMPLE SIZE = 142

MODEL R^2 = 0.9783

MODEL SIGNIFICANCE = <0.0001

Regression Model for the
Aeronautical Engineering Program

<u>VARIABLE</u>	<u>WEIGHT</u>	<u>SIGNIFICANCE</u>
INTERCEPT	1.5978	<0.0001
UGPA	0.2178	<0.0001
GREQ	0.0045	<0.0001
GRET	-0.0017	<0.0001

SAMPLE SIZE = 325

MODEL R^2 = 0.4584

MODEL SIGNIFICANCE = <0.0001

Regression Model for the
Computer Science Program

VARIABLE	WEIGHT	SIGNIFICANCE
INTERCEPT	1.6520	<0.0001
UGPA	0.1510	<0.0001
GRET	-0.0069	<0.0001
GREQ	0.0078	<0.0001
GREM	0.0017	<0.0001
GREV	0.0067	<0.0001

SAMPLE SIZE = 307

MODEL R^2 = 0.6025

MODEL SIGNIFICANCE = <0.0001

Regression Model for the
Electrical Engineering Program

<u>VARIABLE</u>	<u>WEIGHT</u>	<u>SIGNIFICANCE</u>
INTERCEPT	1.5689	<0.0001
UGPA	0.2303	<0.0001
GRET	-0.0129	<0.0001
GREQ	0.0145	<0.0001
GREM	0.0005	<0.0001
GREV	0.0127	<0.0001

SAMPLE SIZE = 645

MODEL R^2 = 0.5476

MODEL SIGNIFICANCE = <0.0001

Regression Model for the
Electro-Optical Engineering Program

<u>VARIABLE</u>	<u>WEIGHT</u>	<u>SIGNIFICANCE</u>
INTERCEPT	1.4797	<0.0001
UGPA	0.1730	0.0137
GRET	-0.0006	0.0459
GREQ	0.0031	<0.0001

SAMPLE SIZE = 106

MODEL R^2 = 0.3591

MODEL SIGNIFICANCE = <0.0001

Regression Model for the
Engineering Physics Program

<u>VARIABLE</u>	<u>WEIGHT</u>	<u>SIGNIFICANCE</u>
INTERCEPT	0.8697	0.0092
UGPA	0.3825	<0.0001
GRET	-0.0078	<0.0001
GREQ	0.0098	<0.0001
GREV	0.0078	<0.0001

SAMPLE SIZE = 165

MODEL R^2 = 0.4460

MODEL SIGNIFICANCE = <0.0001

Regression Model for the
Nuclear Engineering Program

<u>VARIABLE</u>	<u>WEIGHT</u>	<u>SIGNIFICANCE</u>
INTERCEPT	0.3331	0.0941
UGPA	0.1743	0.0334
GREQ	0.0029	<0.0001
GREV	0.0008	0.0168

SAMPLE SIZE = 120

MODEL R^2 = 0.4899

MODEL SIGNIFICANCE = <0.0001

Regression Model for the
Operations Research Program

VARIABLE	WEIGHT	SIGNIFICANCE
INTERCEPT	1.8331	<0.0001
UGPA	0.1612	<0.0001
GRET	-0.0011	<0.0001
GREQ	0.0030	<0.0001
GREX	0.0010	<0.0001

SAMPLE SIZE = 212

MODEL R^2 = 0.4954

MODEL SIGNIFICANCE = <0.0001

Regression Model for the
Systems Engineering Program

<u>VARIABLE</u>	<u>WEIGHT</u>	<u>SIGNIFICANCE</u>
INTERCEPT	0.9307	<0.0001
GRET	-0.0074	<0.0001
GREQ	0.0095	<0.0001
GREV	0.0095	<0.0001

SAMPLE SIZE = 89

MODEL R^2 = 0.8045

MODEL SIGNIFICANCE = <0.0001

Regression Model for the
Strategy and Tactics Program

<u>VARIABLE</u>	<u>WEIGHT</u>	<u>SIGNIFICANCE</u>
INTERCEPT	1.4569	<0.0001
UGPA	0.1731	<0.0001
GREQ	0.0020	<0.0001
GREV	0.0004	0.0096

SAMPLE SIZE = 182

MODEL R^2 = 0.5155

MODEL SIGNIFICANCE = <0.0001

Regression Model for the
Space Operations Program

<u>VARIABLE</u>	<u>WEIGHT</u>	<u>SIGNIFICANCE</u>
INTERCEPT	1.5948	<0.0001
UGPA	0.2127	0.0009
GREQ	0.0019	<0.0001

SAMPLE SIZE = 133

MODEL R^2 = 0.3365

MODEL SIGNIFICANCE = <0.0001

Regression Model for the
Computer Engineering Program

<u>VARIABLE</u>	<u>WEIGHT</u>	<u>SIGNIFICANCE</u>
INTERCEPT	2.5294	<0.0001
UGPA	0.3436	0.0356

SAMPLE SIZE = 21

MODEL R^2 = 0.2025

MODEL SIGNIFICANCE = 0.0356

Regression Model for the
Acquisition Logistics Program

<u>VARIABLE</u>	<u>WEIGHT</u>	<u>SIGNIFICANCE</u>
INTERCEPT	3.6352	<0.0001
GMATV	0.0129	0.0047
GMATQ	-0.0149	<0.0001

SAMPLE SIZE = 106

MODEL R^2 = 0.2000

MODEL SIGNIFICANCE = <0.0001

Regression Model for the
Contracting Management Program
(Using UGPA and GRE scores only)

<u>VARIABLE</u>	<u>WEIGHT</u>	<u>SIGNIFICANCE</u>
INTERCEPT	2.6462	<0.0001
GRET	-0.0025	0.0693
GREQ	0.0024	0.0805
GREa	0.0015	<0.0001
GREV	0.0030	0.0366

SAMPLE SIZE = 167

MODEL R^2 = 0.3381

MODEL SIGNIFICANCE = <0.0001

Regression Model for the
Contracting Management Program
(Using UGPA and GMAT scores only)

<u>VARIABLE</u>	<u>WEIGHT</u>	<u>SIGNIFICANCE</u>
INTERCEPT	5.3264	<0.0001
GMATQ	0.1412	<0.0001
GMATV	0.1753	<0.0001
GMATT	-0.0220	<0.0001

SAMPLE SIZE = 167

MODEL R^2 = 0.3314

MODEL SIGNIFICANCE = <0.0001

Regression Model for the
Engineering Management Program
(Using UGPA and GRE scores only)

VARIABLE	WEIGHT	SIGNIFICANCE
INTERCEPT	2.5175	<0.0001
UGPA	0.1107	0.0003
GRET	-0.0006	0.0003
GREQ	0.0014	<0.0001
GREB	0.0010	<0.0001

SAMPLE SIZE = 269

MODEL R^2 = 0.3531

MODEL SIGNIFICANCE = <0.0001

Regression Model for the
Engineering Management Program
(Using UGPA and GMAT scores only)

<u>VARIABLE</u>	<u>WEIGHT</u>	<u>SIGNIFICANCE</u>
INTERCEPT	2.7416	<0.0001
UGPA	0.1186	<0.0001
GMATQ	0.0339	<0.0001
GMATT	-0.0011	<0.0001

SAMPLE SIZE = 269

MODEL R^2 = 0.4729

MODEL SIGNIFICANCE = <0.0001

Regression Model for the
Logistics Management Program
(Using UGPA and GRE scores only)

<u>VARIABLE</u>	<u>WEIGHT</u>	<u>SIGNIFICANCE</u>
INTERCEPT	1.8289	<0.0001
UGPA	0.0826	<0.0001
GRET	-0.0251	<0.0001
GREQ	0.0267	<0.0001
GREA	0.0002	0.0289
GREV	0.0258	<0.0001

SAMPLE SIZE = 543

MODEL R^2 = 0.8574

MODEL SIGNIFICANCE = <0.0001

Regression Model for the
Logistics Management Program
(using UGPA and GMAT scores only)

<u>VARIABLE</u>	<u>WEIGHT</u>	<u>SIGNIFICANCE</u>
INTERCEPT	3.8533	<0.0001
UGPA	0.1477	<0.0001
GMATV	0.1939	<0.0001
GMATQ	0.1623	<0.0001
GMATT	-0.0226	<0.0001

SAMPLE SIZE = 543

MODEL R^2 = 0.7126

MODEL SIGNIFICANCE = <0.0001

Regression Model for the
Maintenance Management Program
(Using UGPA and GRE scores only)

<u>VARIABLE</u>	<u>WEIGHT</u>	<u>SIGNIFICANCE</u>
INTERCEPT	1.8759	<0.0001
GREQ	0.0013	<0.0001
GREA	0.0006	0.0035
GREV	0.0012	<0.0001

SAMPLE SIZE = 90

MODEL R^2 = 0.7954

MODEL SIGNIFICANCE = <0.0001

Regression Model for the
Systems Management Program
(Using UGPA and GRE scores only)

<u>VARIABLE</u>	<u>WEIGHT</u>	<u>SIGNIFICANCE</u>
INTERCEPT	1.0013	<0.0001
GRET	-0.0098	<0.0001
GREV	0.0095	<0.0001
GREQ	0.0123	<0.0001
GREA	0.0017	<0.0001

SAMPLE SIZE = 299

MODEL R^2 = 0.7200

MODEL SIGNIFICANCE = <0.0001

Regression Model for the
Systems Management Program
(using UGPA and GMAT scores only)

VARIABLE	WEIGHT	SIGNIFICANCE
INTERCEPT	3.9322	<0.0001
UGPA	-0.1509	0.0029
GMATV	0.1041	<0.0001
GMATQ	0.0764	<0.0001
GMATT	-0.1074	<0.0001

SAMPLE SIZE = 299

MODEL R^2 = 0.4495

MODEL SIGNIFICANCE = <0.0001

Regression Model for the
Cost Analysis Program
(Using UGPA and GRE scores only)

<u>VARIABLE</u>	<u>WEIGHT</u>	<u>SIGNIFICANCE</u>
INTERCEPT	1.0611	0.0002
UGPA	0.2924	<0.0001
GRET	-0.0010	<0.0001
GREQ	0.0042	0.0379

SAMPLE SIZE = 56

MODEL R^2 = 0.7323

MODEL SIGNIFICANCE = <0.0001

Regression Model for the
Cost Analysis Program
(using UGPA and GMAT scores only)

<u>VARIABLE</u>	<u>WEIGHT</u>	<u>SIGNIFICANCE</u>
INTERCEPT	1.8418	<0.0001
GMATV	0.0268	<0.0001
GMATT	0.0017	0.0049

SAMPLE SIZE = 56

MODEL R^2 = 0.6739

MODEL SIGNIFICANCE = <0.0001

Regression Model for the
Information Resources Program

<u>VARIABLE</u>	<u>WEIGHT</u>	<u>SIGNIFICANCE</u>
INTERCEPT	2.6125	<0.0001
UGPA	0.1392	0.0552
GRE	0.0010	0.0034

SAMPLE SIZE = 47

MODEL R^2 = 0.2155

MODEL SIGNIFICANCE = 0.0043

Bibliography

1. Air Force Institute of Technology. Financial Report 096CR, unpublished funds report, AFIT/ACB, Wright Patterson AFB OH, 1982.
2. Anastasi, Anne. Psychological Testing (Fifth edition). New York: Macmillan, 1982.
3. Baird, Leonard L. Comparative prediction of first year graduate and professional school grades in six fields. Educational and Psychological Measurement, 35: 941-946 (1975).
4. Borg, Walter R. GRE aptitude scores as predictors of GPA for graduate students in education. Educational and Psychological Measurement, 23: 379-382 (1963).
5. Brogden, Hubert E., On the interpretation of the correlation coefficient as a measure of predictive efficiency. The Journal of Educational Psychology, 37: 65-76 (February, 1946).
6. Bruno, Capt Daniel V. Determining Predictors of Success for the United States Army's Fully Funded Graduate Program. MS thesis, AFIT/GIR/LSR/87D-2. School of Systems and Logistics, Air Force Institute of Technology (AU), Wright-Patterson AFB OH, December 1987.
7. Camp, Joseph and Thomas Clawson. The relationship between the Graduate Record Examinations Aptitude Test and graduate grade point average in a master of arts in counseling program. Educational and Psychological Measurement, 39: 429-431 (1979).
8. Chronbach, Lee J. Essentials of Psychological Testing (Third Edition). New York: Harper & Row, Publishers, Inc., 1973.
9. Covert, Robert W. and Norman M. Chansky. The moderator effect of undergraduate grade point average in the prediction of success in graduate education. Educational and Psychological Measurement, 35: 947-950 (1975).
10. Department of the Air Force. USAF Formal Schools Catalog. AFR 50-5. Washington DC: HQ USAF, 1 March 1989.
11. Dick, Walter and Nancy Hagerty. Topics in Measurement. New York: McGraw-Hill, Inc., 1971.

12. Eckhoff, Constance M. Predicting graduate success at Winona State College. Educational and Psychological Measurement, 26: 483-485 (1966).
13. Educational Testing Service. GRE 1981-1982: Guide to the use of the Graduate Record Examinations, Princeton New Jersey: Educational Testing Service, 1981.
14. Emory, William. Business Research Methods (Third Edition). Homewood IL: Richard D. Irwin, Inc., 1985.
15. Furst, Edward J. Theoretical problems in the selection of students for professional schools. Educational and Psychological Measurement, 10: 637-653 (1950).
16. Green, Bert F. A Primer of testing. American Psychologist, 36: 1001-1011 (October 1981).
17. Guion, Robert M. Personnel Testing. New York: McGraw-Hill, Inc., 1965.
18. Hartnett, Rodney T. and Warren W. Willingham. The Criterion Problem: What measure of success in Graduate Education? Princeton NJ: Educational Testing Service, 1979.
19. King, Donald C. and Robert O. Besco. The Graduate Record Examination as a selection device for graduate research fellows. Educational and Psychological Measurement, 20: 853-856 (1960).
20. Kirnan, Jean P. and Kurt F. Geisinger. The prediction of graduate school success in psychology. Educational and Psychological Measurement, 41: 815-818 (1981).
21. Lent, Richard H. and others. Predictors, criteria, and significant results. Personnel Psychology, 24: 519-533 (1971).
22. Lin, Pang-chieh and Lloyd G. Humphreys. Predictions of Academic Performance in graduate and professional school. Applied Psychological Measurement, 2: 249-257 (1977).
23. Livingston, Samuel A. and Nancy J. Turner. Effectiveness of the Graduate Record Examination for predicting first year grades Princeton NJ: Educational Testing Service, 1982.
24. Madaus, George F. and John J. Walsh. Departmental differentials in the predictive validity of the Graduate Record Examination Aptitude tests. Educational and Psychological Measurement, 4: 1105-1110 (1965).

25. Mehrabian, Albert. Undergraduate ability factors in relation to graduate performance. Educational and Psychological Measurement, 29: 409-419 (1969).
26. Michael, William B. and others. The prediction of success in graduate work in chemistry from scores on the Graduate Record Examination. Educational and Psychological Measurement, 4: 859-861 (1960).
27. Michels, Walter C. Graduate Record Examinations Advanced Physics test as a predictor of performance. American Journal of Physics, 34: 862-866 (1966).
28. Nagi, John L. Predictive validity of the Graduate Record Examination and the Miller Analogies Tests. Educational and Psychological Measurement, 35: 471-472 (1975).
29. Robertson, Malcom and Everett Hall. Predicting success in graduate study. Journal of General Psychology, 71: 359-365 (1964).
30. Robertson, Malcom and Winnifred Nielsen. The Graduate Record Examination and the selection of graduate students. American Psychologist, 16: 648-650 (1961).
31. Sleeper, Mildred L. Relationships of scores on the Graduate Record Examination to grade point averages of graduate students in occupational therapy. Educational and Psychological Measurement, 21: 1039-1040 (1961).
32. Thacker, Andrew J. and Robert E. Williams. The relationship of the Graduate Record Examination to grade point average and success in graduate school. Educational and Psychological Measurement, 34: 939-944 (1974).
33. Thorndike, R. L., Personnel Selection: Test Measurement and Techniques, New York: John Wiley and Sons, Inc., 1949.
34. Traxler, Arthur E. Tests for graduate students. Journal of Higher Education, 23: 473-482 (1952).
35. Van Scotter, James R. Predictors of success in Air Force Institute of Technology residents Master's degree programs: a validity study. MS thesis, AFIT/LSSR 4-83. School of Systems and Logistics, Air Force Institute of Technology (AU), Wright-Patterson AFB OH, September 1983.

36. Willingham, Warren W. Predicting Success in Graduate Education. Science, 183: 273-278 (January 1974).

Vita

Captain Kevin W. Buckley [REDACTED]
[REDACTED]
[REDACTED]

[REDACTED] attended Saint Joseph's University in Philadelphia, from which he received the degree of Bachelor of Science in Chemistry in May 1983. Following his attendance of the Officer Training School, where he was commissioned a Second Lieutenant in August 1983, he was assigned as a undergraduate student at the Air Force Institute of Technology where he received the degree of Bachelor of Science in Aeronautical Engineering in March 1985. He then served as a Space Shuttle Integration Engineer at HQ Space Division, Los Angeles AFB from 1985 to 1988. Captain Buckley returned to AFIT as a graduate student in the School of Systems and Logistics in May 1988.

[REDACTED]
[REDACTED]
[REDACTED]

UNCLASSIFIED

SECURITY CLASSIFICATION OF THIS PAGE

REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1a. REPORT SECURITY CLASSIFICATION UNCLASSIFIED		1b. RESTRICTIVE MARKINGS	
2a. SECURITY CLASSIFICATION AUTHORITY		3. DISTRIBUTION / AVAILABILITY OF REPORT Approved for public release; distribution unlimited	
2b. DECLASSIFICATION / DOWNGRADING SCHEDULE			
4. PERFORMING ORGANIZATION REPORT NUMBER(S) AFIT/GSM/LSR/89S-2		5. MONITORING ORGANIZATION REPORT NUMBER(S)	
6a. NAME OF PERFORMING ORGANIZATION School of Systems and Logistics	6b. OFFICE SYMBOL (If applicable) AFIT/LSY	7a. NAME OF MONITORING ORGANIZATION	
6c. ADDRESS (City, State, and ZIP Code) Air Force Institute of Technology Wright-Patterson AFB OH 45433		7b. ADDRESS (City, State, and ZIP Code)	
8a. NAME OF FUNDING / SPONSORING ORGANIZATION	8b. OFFICE SYMBOL (If applicable)	9. PROCUREMENT INSTRUMENT IDENTIFICATION NUMBER	
8c. ADDRESS (City, State, and ZIP Code)		10. SOURCE OF FUNDING NUMBERS	
		PROGRAM ELEMENT NO.	PROJECT NO.
		TASK NO.	WORK UNIT ACCESSION NO.
11. TITLE (Include Security Classification) AN EVALUATION OF THE AIR FORCE INSTITUTE OF TECHNOLOGY STUDENT SELECTION CRITERIA			
12. PERSONAL AUTHOR(S) Kevin W. Buckley, B.S., B.S., Captain, USAF			
13a. TYPE OF REPORT MS Thesis	13b. TIME COVERED FROM _____ TO _____	14. DATE OF REPORT (Year, Month, Day) 1989 September	15. PAGE COUNT 121
16. SUPPLEMENTARY NOTATION			
17. COSATI CODES		18. SUBJECT TERMS (Continue on reverse if necessary and identify by block number)	
FIELD	GROUP	SUB-GROUP	
5	8		
		Graduate School Air Force Training Selection Psychological Measurement Performance Tests	
19. ABSTRACT (Continue on reverse if necessary and identify by block number)			
Thesis Advisor: Guy S. Shane, PhD Associate Professor of Organizational Behavior and Management			
Approved for public release: IAW AFR 190-1. <i>Larry W. Emmelhainz</i> LARRY W. EMMELHAINZ, Lt Col, USAF 14 Oct 89 Director of Research and Consultation Air Force Institute of Technology (AU) Wright-Patterson AFB OH 45433-6583			
20. DISTRIBUTION / AVAILABILITY OF ABSTRACT <input checked="" type="checkbox"/> UNCLASSIFIED/UNLIMITED <input type="checkbox"/> SAME AS RPT <input type="checkbox"/> DTIC USERS		21. ABSTRACT SECURITY CLASSIFICATION UNCLASSIFIED	
22a. NAME OF RESPONSIBLE INDIVIDUAL Guy S. Shane, PhD		22b. TELEPHONE (Include Area Code) (513) 255-2820	22c. OFFICE SYMBOL AFIT/LSR

UNCLASSIFIED

Block 19. Abstract (Continued)

This thesis was designed to evaluate the suitability of the variables that AFIT uses to select graduate students. The objective was to determine if, indeed, these variables are effective at predicting graduate school academic success at AFIT.

This study examined the records of 4170 US military officers, foreign officers, and civilians who attended in-residence AFIT graduate programs from 1977 to 1987. From these records was obtained data on each students' undergraduate GPA and scores on standardized tests, which AFIT currently uses in the selection process.

Using the graduate GPA as the criterion, this study examined the effectiveness of these predictors with correlation analysis. In addition to studying the student population as a whole, the sample was also broken down to see if the predictors were equally suitable across all programs.

This study found that all predictors were significantly correlated with graduate GPA and thus were suitable for use in the selection process. In addition, the study found that all predictors were not equally effective in predicting academic performance in all programs. Using the best set of significantly correlated variables, predictive models were developed for each program. The admissions office should use each model to select students on a program-by-program basis.

UNCLASSIFIED